CROSS-SCALE ANALYSIS IN CLASSIFICATION AND SEGMENTATION OF MOVEMENT

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Dissertation
Cross-scale analysis in classification and segmentation of movement

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Summary

Movement is the essence of many spatiotemporal phenomena around us. Recent advances in tracking technologies have enabled the collection of tremendous amounts of movement trajectory data. Following in the footsteps of data production, computational methods are being developed in order to extract meaningful patterns from the raw movement data. These patterns, in return, can be related to valuable information about the behaviors of the moving objects under study. However, due to the internal and external factors influencing movement, the behaviors maybe compounds of different patterns at various spatial and temporal scales.

The focus of this thesis therefore lies on investigating the importance of scale and cross-scale analysis in two movement analysis tasks, namely movement classification and trajectory segmentation. In movement classification, the aim is to build a classification model by finding relationships and rules among movement features in order to assign the input data to known classes. In trajectory segmentation, however, the aim is to decompose a movement trajectory into segments of homogenous movement characteristics. These characteristics can be measured by different geometrical, physiological or semantic properties of movement. The relevance of these two analysis tasks are highly recognized in the literature, however, the consideration of cross-scale aspects has the advantage to improve the commonly used single-scale approaches in the tasks of movement classification and trajectory segmentation.

The main contribution of this thesis lies in introducing new methodologies for cross-scale movement analysis. In movement classification, we employed a resampling method for an improvement computation of movement parameters across different temporal scales as input features in the classification. Moreover, the use of discrete wavelet transform (DWT), as another multi-scale measure, is investigated to provide complementary features in movement classification. DWT is further used in trajectory segmentation, where the provided decomposition levels of DWT is used to investigate the variations in movement patterns across different scales.

In the addressed tasks, this thesis shows that cross-scale analysis is needed in order to define an analysis scale which matches better to the scale of phenomena under study and that employing such methods yields better-quality results compared to single-scale analysis. The importance of cross-scale analysis was revealed by application on various movement datasets in real-world applications such as neuropharmacology, behavioral ecology, and biology.

Zusammenfassung

Bewegung ist der Kern vieler uns umgebender, raumzeitlicher Phänomene. Dank der jüngsten Entwicklungen im Bereich der Tracking-Technologie können Bewegungstrajektorien im grossen Umfang erfasst werden. Neben der Erfassung der Bewegungstrajektorien liegt der Fokus vor allem auf deren Auswertung mit Hinblick auf der Extrahierung aussagekräftiger Muster, da diese Muster wertvolle Informationen über die sich bewegenden Objekte enthalten können. Die Objektbewegungen können hierbei sowohl durch interne als auch durch externe Faktoren beeinflusst werden, weshalb die extrahierten Muster raumzeitlichen Variationen unterliegen können.

Die vorliegende Arbeit beschäftigt sich mit der Bedeutung skalenbezogener und skalenübergreifender Aspekte für Standardanalysen der Bewegung: zum einen für die Klassifikation von Bewegungsmustern und zum anderen für die Segmentierung von Bewegungstrajektorien. Bei dem Klassifikationsansatz werden Bewegungsmuster aufgrund ihrer spezifischen Eigenschaften in vordefinierte Kategorien eingeordnet. Dahingegen werden bei der Segmentierung die Bewegungstrajektorien zuerst entsprechend charakteristischer Bewegungsmerkmale in homogene Teil-Trajektorien unterteilt und nachfolgend unter Berücksichtigung geometrischer, physiologischer und semantischer Eigenschaften quantitativ ausgewertet. Diese üblicherweise ein-skalig angewandten Standardanalysen entsprechen zwar dem aktuellen Stand der Forschung, haben aber mit Hinblick auf die Berücksichtigung skalenübergreifender Aspekte noch Verbesserungspotential.

Der wichtigste Beitrag der vorliegenden Arbeit ist dementsprechend die Einführung neuer, skalenübergreifender Methoden für die Analyse von Bewegungstrajektorien. Durch den Einsatz von Resampling auf zeitlich unterschiedliche Abtastintervalle konnte die Berechnung der für die Klassifikation von Bewegungsmustern notwendigen Bewegungsparameter deutlich verbessert werden. Darüber hinaus konnten durch die multi-skalige Anwendung der diskreten Wavelet-Transformation (DWT) zusätzliche Merkmale für den Klassifikationsansatz abgeleitet werden. DWT fand zudem Verwendung in der Segmentierung der Bewegungstrajektorien, um skalenübergreifenden Variationen in den Bewegungsmustern zu untersuchen.

Die Ergebnisse zeigen, dass skalenübergreifende Aspekte berücksichtigt werden müssen, damit für die Auswertungen von Bewegungstrajektorien die Skala so definiert werden kann, dass sie bestmöglich der Skala des untersuchten Phänomens entspricht. Eine Integration der in dieser Arbeit entwickelten Methoden in die bestehenden Analysen resultiert in qualitativ besseren

Ergebnissen im Vergleich zu ein-skaligen Anwendungen. Die Bedeutung skalenübergreifender Analysen wurde hierbei anhand praxisorientierter Anwendungen im Bereich Neuropharmakologie, Verhaltensökologie und Biologie verdeutlicht.

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Introduction

1 Introduction

1.1 Motivation

With the pervasive diffusion of location-aware devices, we are witnessing a myriad of movement trajectories available nowadays (Jeung et al. 2011; Zheng 2015). By using this new source of geographic information, different sorts of moving objects are monitored at previously unseen temporal and spatial granularities. The uniqueness of movement lies in its ubiquity, making it a key element of many phenomena in a variety of application domains (Purves et al. 2014): Smartphones are used to infer transportation modes in urban studies (Zheng et al. 2008; Ohashi et al. 2014; Zheng et al. 2014). GPS tags, attached to animals, are used to infer behaviors in movement ecology (Cagnacci et al. 2010; Demšar et al. 2015). WiFi and Bluetooth devices are used in monitoring crowd behavior in large-scale events (Delafontaine et al. 2012; Larsen et al. 2013; Schauer et al. 2014). Video-tracking systems are used for drug screening (Cachat et al. 2011) or species identification (Pennekamp et al. 2015) in studies of biological organisms. In these and other applications, understanding movement helps in capturing the dynamic processes of great socioeconomic relevance (Gudmundsson et al. 2012).

Despite of the wealth of available movement data, inferring higher level behavioral schemes from such data remains a challenge. In geographic information science (GIScience) and related fields, there has been a significant increase in development of methods to discover latent information from raw movement data. Among the analysis techniques addressed by current methodological research, this thesis seeks to investigate the importance of *scale* and *cross-scale analysis* in two movement analysis tasks, namely *movement classification* and *trajectory segmentation*.

In movement classification, the aim is to build a classification model based on the classes of known trajectories in order to assign the classes of unknown ones. The classes can be assigned to either the entire trajectory level or sub-trajectories. The classifier finds the relationships and rules between derivatives of movement (referred to as movement *features*), while putting aside the original shape (i.e. geometry). However in trajectory segmentation, the aim is to decompose the movement trajectory into segments of homogeneous movement characteristics (Buchin et al. 2011). Segmentation hence can be essentially done based on multiple properties, including geometrical properties, semantics of embedding context or physiological properties extracted from other sensors.

Due to the effect of internal and external factors influencing the movement at different spatial and temporal scales, behaviors may result in compounds of different patterns at various scales (Nathan et al. 2008). These internal and external factors, and the resulting movement patterns, are therefore likely to be valid within their own *spatial and temporal scale ranges* at which they are manifested. However, as in any other phenomenon embedded in space and time (Turchin 1998), scale is a problematic issue in movement and the intertwining notions of spatial and temporal scales make the interpretation of scale even more complex (Goodchild 2011; Jed A Long & Nelson 2013). This is due to the fact that scale is both a spatial and a temporal property in movement and these two properties may reflect the trajectory data or the space of the movement process (Soleymani et al. 2014[a]). The spatial separation of observation points along a movement trajectory affects the temporal sampling granularity, and vice versa (Laube & Purves 2011). Therefore and as evident from the literature, using only the original temporal granularity at which the data is captured is a strong oversimplification of the actual movement patterns, assuming that these patterns are present at every spatiotemporal scale examined (Fryxell et al. 2008; Laube & Purves 2011). Yet, almost all movement analysis that is reported in the literature today is restricted to a single analysis scale, and usually to the original temporal granularity. Clearly, adequate methods for movement analysis should be capable of extracting patterns *across* different spatiotemporal (as opposed to only spatial or only temporal) scales, to investigate the relationships between form and process (Levin 1992). Determining the scale of process (i.e. phenomena) is a major goal in geographic disciplines and matching the analysis scale to the actual scale of phenomena triggers the development of multi-scale analysis approaches (Montello 2001).

Recognizing the importance of scale and **cross-scale analysis**, two analysis approaches are pursued in this thesis in order to address the movement classification and trajectory segmentation problems mentioned above. Firstly, the effect of calculating MPs across different window sizes are investigated. Secondly, by employing the discrete wavelet transform (DWT) on the profiles of MPs, the variations of movement patterns at different scales are monitored. As there is no practical evidence that using a single-scale analysis will necessarily yield the optimal results, this thesis investigates whether cross-scale analysis in movement yields superior results compared to single-scale analysis. This hypothesis was tested in movement classification by changing the spatial and temporal scales at which the movement features are computed. This will lead to choose an analysis scale yielding higher-quality results (in this case classification performance) compared to single-scale analysis. Similarly in segmentation, the hypothesis was tested by investigating whether analyzing the

MP profiles using DWT decomposition will give better results in terms of the number of extracted segments and also how well do they match to the expert annotations.

In both of these analysis tasks, a *supervised learning* approach is employed, in the sense that the outputs of the analysis are validated based on the ground truth data (Witten & Frank 2005). In movement classification, the performance of classifier function is validated by comparing to the labels of training set. Similarly in segmentation, the resulting segments are validated by comparing to annotated segments representing behaviors given by the domain experts.

This introductory chapter starts with giving an overview of movement research in GIScience (Section 1.2), followed by the addressed analysis tasks, i.e. movement classification (Section 1.3) and trajectory segmentation (Section 1.4). The importance of cross-scale analysis and the employed methods to address scaling issues are described in Section 1.5 and the case studies are explained in Section 1.6. The chapter ends by defining the objectives and the research questions (Section 1.7) and finally providing an overview of the structure of the thesis in Section 1.8.

1.2 Movement research in GIScience

In GIScience, the presence of movement data takes a prominent role in advancing the static perspective of GIScience toward a more dynamic view of the world (Laube 2015). The movement of an individual can be represented by its *trajectory*, as a time-ordered sequence of positions (Spaccapietra et al. 2008). Moreover for each fix of the trajectory, a set of measurable quantities of movement, referred to as *movement parameters* (MPs), are calculated. The focus in this thesis is on relative (or interval) MPs, where the values are measured over time intervals, such as speed, turning angle and path sinuosity (Laube et al. 2007; Giannotti & Pedreschi 2008; Dodge et al. 2008).

Alongside the increasing amounts of geographic data, the most remarkable advances in geographic knowledge discovery have taken place in spatiotemporal and moving object databases (Miller & Han 2009). In movement analysis, accordingly, a new field of research known as ‘Computational Movement Analysis’ (Gudmundsson et al. 2012; Laube 2014) has developed, in response to the prevalent research interest in developing analysis methods for movement data. This includes, to name but a few, modeling moving objects and their collective dynamics (Galton 2005), semantic trajectory analysis (Parent et al. 2013), visual analytics of movement (von Landesberger et al. 2012; Andrienko and Andrienko 2012), similarity assessment of movement (Dodge et al. 2012; Buchin et al. 2014) and cross-scale movement analysis (Laube & Purves 2011; Postlethwaite et al. 2012; Soleymani et al. 2014[a]).

Simultaneously, various taxonomies for the analysis of movement patterns have been proposed providing a baseline for the coordination of method development in movement research. Giannotti and Pedreschi (2008) introduced three main steps for knowledge discovery from movement databases, including trajectory reconstruction, knowledge extraction, and knowledge delivery. While their taxonomy enumerates the general steps involved in knowledge extraction from movement data, Laube (2009) introduced a framework focusing on the movement pattern mining methods. The framework is following the well-established functionalities of data mining methods into four categories of: class/concept description; finding frequent patterns, rules, associations and correlations; classification and clustering. Dodge et al. (2008) developed a further taxonomy of movement patterns by dividing them into generic and behavioral categories. Their taxonomy includes higher-detailed categories by investigating the properties of movement patterns including their embedding dimension, number of moving objects involved and the influencing factors on movement. Yet another conceptual framework with an exclusive focus on visual analytics was proposed by Andrienko et al. (2011), which is out of the scopes of this work.

From the above-mentioned analysis categories, this thesis seeks to investigate the contributions of cross-scale analysis in two areas: First, classification of movement patterns and behaviors and second, segmentation of movement trajectories.

1.3 Movement classification

Classification is denoted as “finding rules or methods to assign data items to pre-existing classes” (Miller and Han 2009, p.7). As a supervised learning approach, the inputs (known as input features) are given together with their desired outputs (known as labels or classes) and the idea is to find relationships to assign input features to the classes. For evaluating the performance of a classification model, the input labelled data is divided into a training set and a test set, where the classification model is first built using the training data and validated by applying on the test set. The outcome of such analysis can be ultimately used in order to predict the classes of unknown cases.

In this thesis, movement classification is referred to as a particular set of problems, where either the entire movement trajectory or segmented trajectories are assigned to known classes. Examples of these classes are distinguishing between recreational cyclers and regular commuters in transportation studies or different behaviors along a bird trajectory (e.g. flying, foraging and other modes). Therefore, labeled trajectories are needed as training and validation data in which the classes are known. Generating such labels is generally a labor-intensive task, either by direct field observation of the moving object or manual interpretation of the expert (Shamoun-Baranes et al. 2012). A classification model is built based on the movement characteristics of labeled trajectories in order to infer criteria to reliably predict the class of unlabeled cases.

The process of building classification models based on known movement data has many real-world applications. For example, classification of different vessel types from satellite images (Greidanus & Kourti 2006), detection of anomalous trajectories in video-surveillance footage (Naftel & Khalid 2006), analysis of the movement of players in sports (Grunz et al. 2009; Gudmundsson & Wolle 2010), learning movement types in transportation studies (Dodge et al. 2009; Gennady Andrienko et al. 2011; Torrens et al. 2011; Li 2014), behavioral classification of animal trajectories (Shamoun-Baranes et al. 2012) and species identification in biological studies (Amer et al. 2011; Joo et al. 2013; Pennekamp et al. 2015; Soleymani et al. 2015).

In movement classification, several steps need to be taken in order to transform the observational movement data to the final classes. After computation of MPs from raw trajectory data, 'profiles' of MPs are obtained. Since after computation of MP_i, trajectories have been transformed into functions of the type $MP_i = f(t)$, an MP profile is equivalent to the time series of a movement parameter. In the next feature extraction step, quantitative measures (e.g. statistical descriptors) of MP profiles are used in order to obtain a set of vectors as input features for the classification. Generating discriminative features is an essential task in movement classification, as these features will ideally distinguish the core characteristics of the movement classes (Lee et al. 2008). The most common form of these features are statistical descriptors (i.e. mean, standard deviation, median, etc.). However, it is not known how efficient these features are to distinguish between movement classes at different scales. More specifically how computing MPs at different window sizes can affect the values of those features and consequently the obtained classification results. Moreover, due to the fact that these features are computed based on basic statistical measures, they can capture only limited aspects of movement and therefore some movement patterns may go undetected. As part of the cross-scale analysis introduced in this thesis, more advanced features are integrated in the classification model. This is done firstly by computation of MPs across different window sizes and investigating how the classification performance is changing accordingly. And second, advanced features based on DWT are used in order to investigate further movement patterns (i.e. periodicity patterns or abrupt variations) in the MP profiles (see Section 1.4).

The classification model is built afterwards by using the relevant features as quantitative inputs for the model and relating these to the known classes. The contributions of the different movement feature sets are evaluated by the classification accuracies achieved in the classification process. This allows to determine the 'reliable analysis scale', that is, the scale range at which the movement parameters are most reliably computed (i.e. where the best classification accuracy is obtained). Eventually, this results in a movement classification process that establishes the reliable spatiotemporal scales where the optimized classification performance is achieved (Soleymani et al. 2014[a]).

In this thesis, different classification techniques such as *support vector machines* (SVM) and *decision trees* (DT) were used in the addressed movement classification tasks. Also, some other functionalities of machine learning, namely feature selection by the use of *genetic algorithms*, were employed to determine the most contributing movement features to the classification.

1.4 Trajectory segmentation

Trajectory segmentation is similar to movement classification, in the sense that they both aim at grouping parts of trajectories with respect to the similarity in movement properties. In this thesis, trajectory segmentation is referred to as a set of methods aiming at extracting sub-trajectories (i.e. segments) of homogenous movement characteristics, with respect to variations in some properties (e.g. geometrical, semantic or physiological properties (Buchin et al. 2011; Dodge et al. 2012)). These segments can be further investigated to correspond to particular behavioral states. Like classification, the segmentation of movement trajectories has practical applications in a variety of fields in movement research. For example in characterizing transportation modes (Buchin et al. 2008; Zheng et al. 2008; Ohashi et al. 2014), studying the behaviors of tourists (Phithakkitnukoon et al. 2015) or cyclists (Schuessler 2009) in urban areas. Also, a large body of literature is dedicated to inferring behavioral states from animal trajectories (Guilford et al. 2009; Gurarie et al. 2009; Beyer et al. 2013; Nams 2014; Dodge et al. 2014; de Weerd, van Langevelde, van Oeveren, B. a. Nolet, et al. 2015; Gurarie et al. 2015).

According to Zheng (2015), three main categories of methods could be used for trajectory segmentation: 1) using time intervals between trajectory fixes, 2) spatial shape to identify the key points maintaining the shape of the trajectory, and 3) semantic segmentation by further interpretation of the segments to assign meanings (i.e. behaviors) to them. The outputs of the segmentation process are subsections of the original trajectories that satisfy such criteria (Buchin et al. 2011). The focus in this thesis is on the third of Zheng's taxonomy, with the aim of dividing the trajectories into segments with homogeneous movement characteristics, which can point out particular behaviors. It is important to note that in trajectory segmentation, consideration should be given to the fact that the changes in movement characteristics are continuous along the trajectory. In other words, it might not be possible (or highly unlikely) to immediately switch from a certain behavior to another one in the following fix of the trajectory. For example a bird will have to reduce its speed when changing from flying to resting mode. Transitions will be even more gradual and subtle in the case of large moving objects with high inertia, such as moving vessels (Patroumpas et al. 2015). Consequently, the fixes should not be treated independently and the correlation between them should be taken into account. These temporal autocorrelation effects are commonly disregarded in the segmentation methods published to date. Furthermore, the models are suffering from a model misspecification problem by being dependent on a specific movement variable (Gurarie et al. 2015). In this thesis, the capability of DWT is investigated for trajectory segmentation, where the variations in movement patterns can be successively analyzed using different decomposition levels of the DWT. The hierarchical structure of the DWT decomposition can give insight into the cross-scale relationships between movement patterns.

1.5 Cross-scale movement analysis

The influence of scale has been widely discussed in geography. Among the first attempts are modifiable areal unit problem (MAUP) for spatial or MTUP in the case of temporal scale (Openshaw 1984). This has led to development of cross-scale analysis methods in a variety of disciplines (Montello 2001), including using fractals for understanding self-similar phenomena (i.e. coastlines) at different spatial scales (Lam & Quattrochi 1992), or in digital terrain modeling and analysis (Wood 1996; Fisher et al. 2004). Cross-scale analysis has also been widely acknowledged in other areas which are explicitly spatially-aware, such as behavioral ecology where there is a long history of developing methods elucidating the relationship between pattern and scale (Levin 1992; Shamoun-Baranes et al. 2011). Examples are fractal analysis (Fritz et al. 2003; Nams 2005; Webb et al. 2009) or first-passage time (Fauchald and Tveraa 2003; Pinaud 2008).

In GIScience, e*xtent* and *resolution* are the two meanings of scale which are of greatest significance (Goodchild 2011). These two terms are highly relevant, although rarely questioned, in the area of movement analysis (Laube & Purves 2011). However, the abundance of highly granular movement data available nowadays has facilitated, and at the same time necessitated, the development of cross-scale analysis approaches. As a definition, *cross-scale analysis of movement data* refers to methods and algorithms capable of investigating the relationships between patterns and processes that occur at multiple spatial and/or temporal scales of movement (Soleymani et al. 2014[a]). The work by Laube & Purves (2011) is probably the first effort in the GIScience community to systematically explore the effects of calculating the value of MPs across different temporal scales. Not surprisingly, more recent studies in the GIScience delineate the importance of cross-scale analysis in movement. Evidences are developing new multi-scale measures (i.e. multi-scale straightness index (Postlethwaite et al. 2012)), detection of patterns using Brownian bridges in low sampling rate movement data (Buchin et al. 2012), measurement of dynamic interactions in movement (Jed A. Long & Nelson 2013), behavioral classification (Soleymani et al. 2014[a]; Soleymani et al. 2014[b]; de Weerd et al. 2015) and context-aware movement analysis (Gschwend 2015).

In this thesis, the methodology by Laube & Purves (2011) is advanced by integrating features from the spatial domain, as well as computing more advanced features, such as DWT coefficients. Therefore in the movement classification analysis, a methodology was proposed for the classification of movement data that relies on computing and analyzing movement features jointly in both the spatial and temporal domains. Conversely in segmentations, the DWT decomposition was employed to process different movement patterns across different scales.

1.5.1 Calculation of movement parameters across different window sizes

Movement data are prone to positional uncertainty and therefore scale and data quality issues are tightly connected (Laube & Purves 2011). Furthermore, due to the fact that movement patterns are evident at different scale ranges, using the original temporal granularity as the analysis scale for computation of MPs might be too constraining. One way to consider those effects is to calculate the movement parameters not only at the original temporal scale, but to vary the window size at which movement parameters are computed. This can then show to what degree the values of movement parameters vary when derived at a range of temporal scales. Accordingly, at each fix of the trajectory, values of movement parameters are computed across a series of sliding windows with different sizes of *w*, in a segment where *w/2* fixes exist before and after the central sample point of interest (Figure 1.1). This method was originally proposed by Laube and Purves (2011) and the outcomes of such cross-scale analysis were also used to derive classification features in this thesis. This was done by converting the set of MP profiles calculated at different scales to a set of features in the classification model. Investigating the differences in the classification performance based on such cross-scale features allows determining the proper analysis scale (i.e. the 'reliable scale') depending on the classification problem (Soleymani et al. 2014[a]).

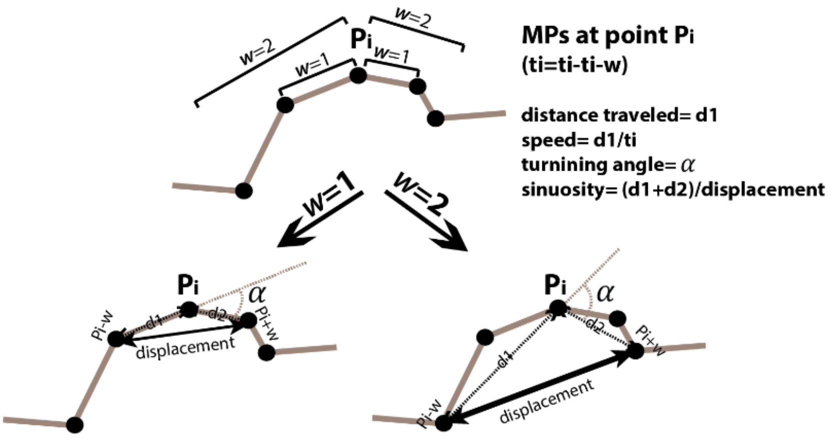

Figure 1.1 Calculation of movement parameters at different temporal window sizes (i.e. *w* = 1, 2, ...)

1.5.2 Discrete wavelet transform on the profile of movement parameters

The wavelet transform is the process of expressing an input signal through a set of functions, by shifting and dilating a single function called the *mother wavelet* (Mallat 1999; Daubechies 1990). The signals considered here are the profiles of movement parameters, which, as observed above, form a function and a time series. Using the discrete wavelet transform (DWT), the signal is passed through a series of high-pass and low-pass filters, yielding a set of coefficients called wavelet coefficients. Thus, it is possible to decompose the input movement signal into high-frequency *detail* sub-bands and low-frequency *approximation* sub-bands at different levels (Figure 1.2). The resulting sub-bands (i.e. approximation and detail) are basically reconstructed based on the wavelet coefficients. The low-pass filter retains only the frequencies lower than a certain threshold, leading to maintain the general structure of the signal. By contrast, high-pass filters allow signals with frequencies higher than the threshold to pass, allowing to capture details of variation in the signal. The decomposition process provides a wide range of decomposition levels in order to investigate the variations in the profile of a movement parameter, which is a convenient way to relate different analysis scales to the behavioral patterns captured in a trajectory. For the purposes of segmentation, the detail coefficients may then be used to investigate abrupt variations in the data, while the approximation coefficients are useful in taking autocorrelation effects into account.

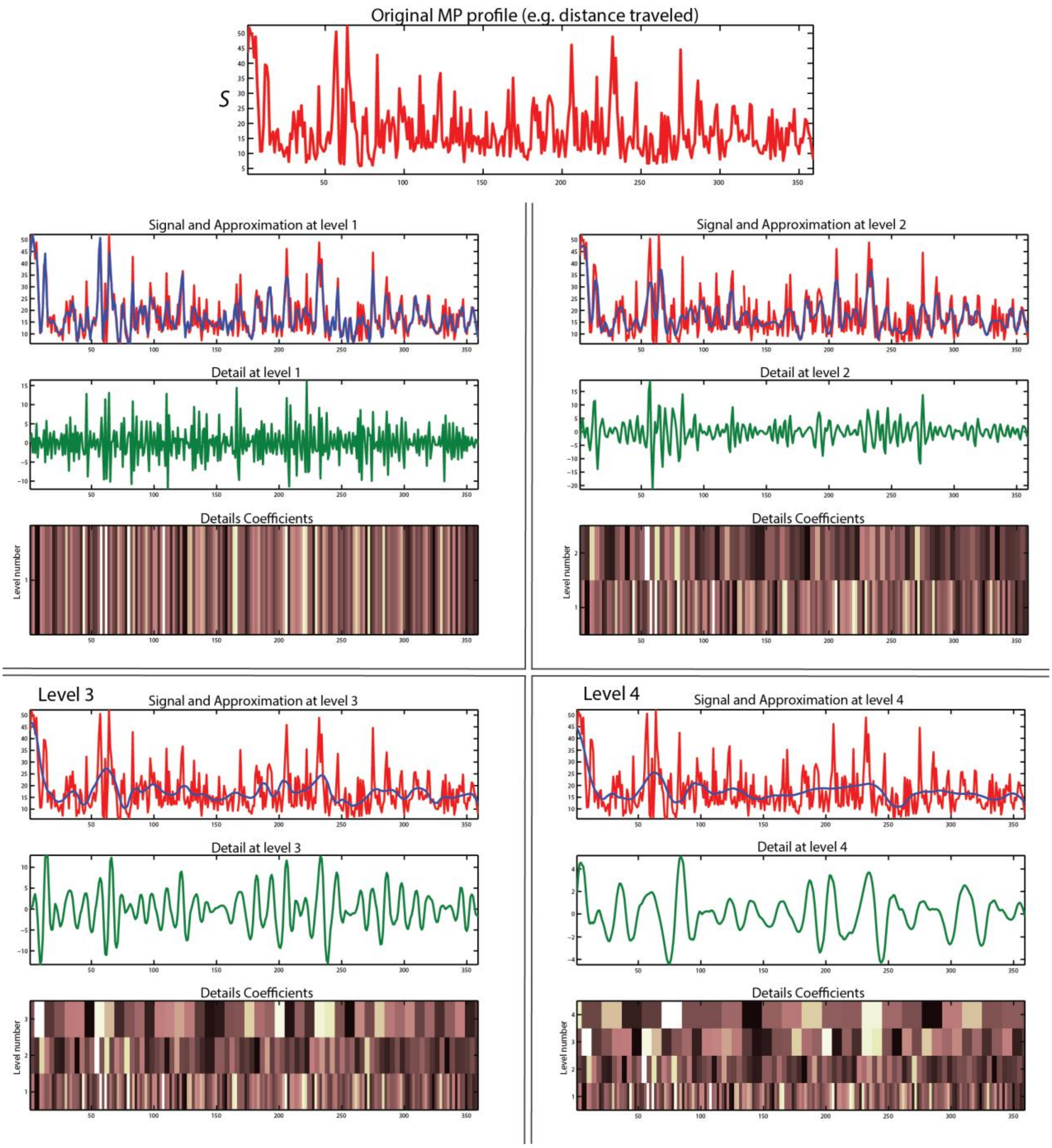

Figure 1.2 Decomposition of a movement parameter profile through wavelet analysis at different levels. The approximation (in blue) and detail (in green) sub-bands as well as the obtained wavelet coefficients are shown for each level.

In this thesis, the possibility of working with both of the coefficient sets and the resulting sub-bands was investigated in the two types of classification problems addressed. In movement classification the wavelet coefficients are used as input features for the classification model (Soleymani et al. 2015). This allows to capture periodicity patterns as well as abrupt changes in movement data, which cannot be captured through other measures (Riotte-Lambert et al. 2013; Benhamou 2014; Sur et al. 2014). This is due to the ability of the wavelet transform to detect non-stationary patterns in movement where the transitions in activity patterns occur only irregularly in the data (Fagan et al. 2013). Moreover, it may also be useful for relating these activities to other factors (e.g. physiological, ecological, contextual, etc.) affecting the movement (Wittemyer et al. 2008; Gaucherel 2011). Thus, in a classification problem, while the global movement features will capture the most general variations in the profiles of movement parameters, the features extracted based on the DWT serve as a complementary tool for identifying periodic patterns or change detection in the data (Soleymani et al. 2015).

On the other hand, in the case of trajectory segmentation, the wavelet sub-bands are used to extract behaviorally consistent segments. The decomposition of a movement signal into multiple levels can give insights about the changes in the respective segments. This will lead not only to observing the movement characteristics at the scale at which the data was originally captured, but investigating such variations in movement patterns at multiple scales becomes feasible. While the detail sub-bands are used to detect abrupt change points in movement behavior, the approximation sub-bands are used to characterize the continuous transitions between different movement bouts.

1.6 Case studies

The developed methodologies were applied on four different real-world datasets, as a demonstration that the proposed methods are generalizable and can essentially be applied to differentiate between categories of interest in different problems. These datasets are summarized in Table 1.1. In all those datasets, the aim was to classify the movement data into different behavioral classes, either in a classification or a segmentation task.

Table 1.1 Description of the real-world datasets used in this thesis

Moving individual	**Number of trajectories**	**Application area**	**Analysis Task**	**Trajectory level**
Zebrafish (*Danio rerio*)	409	Behavioral neuropharmacology	Classification	Entire trajectory
Oystercatcher (*Haematopus ostralegus*)	12	Behavioral ecology	Classification	Segmented trajectory
Ciliates (*Kingdom Protozoa, Alveolata, Ciliophora*)	3957	Experimental biology / Microbiology	Classification	Entire trajectory
Turkey vultures (*Cathartes aura*)	4	Behavioral ecology	Segmentation	Segmented trajectory

1.7 Objectives and research questions

In the transformation of raw movement data into behavioral categories of interest, movement classification and segmentation represent a set of methods to infer precious process knowledge about movement. A large number of algorithms have been introduced in the literature, documenting significant progress of movement classification and trajectory segmentation in GIScience and related sciences. However, there are few evidences of taking the importance of cross-scale analysis in such studies into account (Laube & Purves 2011). The motivation of this thesis stems from the methodological gap in addressing scaling issues in such movement analyses. Therefore, the **main objective** of this thesis is to *develop cross-scale analysis approaches, contributing to the conceptual and methodological knowledge in support of movement classification and trajectory segmentation studies*. The transformation of cross-scale measures into meaningful distinguishing features (in classification) and segments (in segmentation) can have practical applications in a variety of research fields involved in movement analysis, as shown in the addressed case studies.

Research questions

To guide the research of this thesis, three main research questions were formulated. Considering the methodological gaps in cross-scale analysis of movement classification and segmentation tasks, the thesis set out by investigating analytical methods capable of transferring from single-scale to cross-scale movement analysis. A general methodology is introduced for movement classification, where features are extracted at different spatial and temporal scales. The cross-scale analysis is pursued in trajectory segmentation, aiming at investigating the variations in movement patterns expressed along a segment at different scales.

The three research questions, related to the three methodological building blocks of this thesis are outlined below.

- ***RQ 1: General methodology:*** *What are suitable methods to move from single-scale to cross-scale movement analysis?*
- ***RQ 2: Cross-scale classification:*** *Which movement features contribute to multi-scale classification of movement? And to what degree?*
- ***RQ 3: Cross-scale segmentation:*** *How can multilevel decomposition methods contribute to segmentation of trajectories in presence of abrupt and continuous changes in movement?*

1.8 Structure of this thesis

The key principles about movement classification and segmentation and the importance of cross-scale movement analysis were covered in this Chapter. Chapters 2 to 5 form the core of this thesis and are presented through the research papers listed below, addressing the objectives and research questions provided in Section 1.5. Figure 1.3 provides a graphical summary of the position of each paper in the research process and the contributions to the research questions of this thesis.

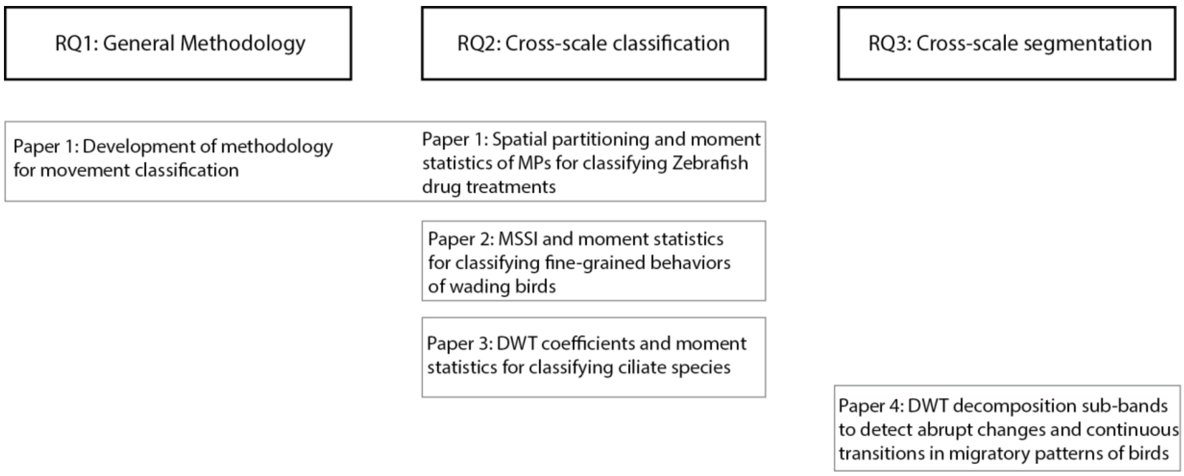

Figure 1.3: Contribution of the research papers to the individual research questions

This thesis is based on four successively research papers published in peer-reviewed international scientific journals and conference proceedings. The four research papers are presented in the following.

Research Paper 1 (Chapter 2):

Soleymani, A., Cachat, J., Robinson, K., Dodge, S., Kalueff, A. V. and Weibel, R. (2014). Integrating cross-scale analysis in the spatial and temporal domains for classification of behavioral movement. *Journal of Spatial Information Science (JOSIS)*, 8(8), 1-25.

Author contributions: Conceived and designed the experiments: JC KR AVK AS. Performed the experiments: JC KR. Analyzed the data: AS JC. Contributed reagents/materials/analysis tools: AS JC SD RW. Wrote the paper: AS JC KR SD AVK RW.

Chapter 2 introduces a general methodology for the classification of behavioral movement data based on measures computed across different scales of the spatial and temporal domains (RQ1 and RQ2). This methodology acts as a baseline for the remainder of the classification of problems addressed in this thesis. As a case study, a video-tracked dataset of adult zebrafish trajectories is analyzed in order to build classification models for different drug treatments.

Research Paper 2 (Chapter 3):

Soleymani, A., van Loon, E. E. and Weibel, R. (2014). Capability of movement features extracted from GPS trajectories for the classification of fine-grained behaviors. *Proceedings of the AGILE'2014 International Conference on Geographic Information Science*, Vol. 3. No. 6.

Author contributions: Conceived and designed the experiments: AS EEL. Performed the experiments: AS EEL. Analyzed the data: AS EEL RW. Contributed reagents/materials/analysis tools: AS EEL RW. Wrote the paper: AS EEL RW.

Chapter 3 investigates the applicability of the proposed methodology for classifying fine-grained foraging behaviors in trajectories of wading birds. This chapter shows that cross-scale analysis makes it possible to detect micro behaviors through movement data alone (RQ2), which would be generally possible only if data from other sensors (i.e. accelerometer) are available.

Research Paper 3 (Chapter 4)

Soleymani, A., Pennekamp, F., Petchey, O.L. and Weibel, R. (2015): Developing and Integrating Advanced Movement Features Improves Automated Classification of Ciliate Species, PLoS ONE, 10(12): e0145345.

Author contributions: Conceived and designed the experiments: AS FP OLP RW. Performed the experiments: FP. Analyzed the data: AS FP. Contributed reagents/materials/analysis tools: AS FP OLP RW. Wrote the paper: AS FP OLP RW.

Chapter 4 extends the capability of the proposed methodology by integrating frequency-based features of movement (RQ2 and RQ3). Therefore, the profiles of MPs are treated as time series which allows performing a DWT on them. Using the example of the classification of different ciliate species, whose movements had been captured from video, it is demonstrated how using this approach leads to further improvement of classification accuracy.

Research Paper 4 (Chapter 5)

Soleymani, A., Pennekamp, F., Dodge, S., and Weibel, R. (2016): Characterizing change points and continuous transitions in movement behaviors using wavelet decomposition. *Methods in Ecology and Evolution* (submitted)

Author contributions: Conceived and designed the experiments: AS SD FP RW. Performed the experiments: AS. Analyzed the data: AS FP RW. Contributed reagents/materials/analysis tools: AS FP SD RW. Wrote the paper: AS FP SD RW.

Chapter 5 investigates the lessons learned from the preceding classification problem, in order to employ the DWT in a segmentation problem. This chapter shows how an inherently multi-scale analysis tool (i.e. the DWT) can be used for exploring the relationship between behaviors and scale in movement (RQ3). A dataset of trajectories of long-haul migratory birds (i.e. turkey vultures) as well as a simulated dataset are used to demonstrate the applicability of the proposed DWT-based segmentation algorithm.

Chapter 6 concludes this thesis by summarizing and discussing the main findings in relation to the problem setting outlined in this chapter, also providing an outlook on possible future research.

Chapter

2

Integrating cross-scale analysis in the spatial and temporal domains for classification of behavioral movement

Soleymani, A., Cachat, J., Robinson, K.,
Dodge, S., Kalueff, A. V. and Weibel, R.

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Research Article

Integrating cross-scale analysis in the spatial and temporal domains for classification of behavioral movement

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Abstract: Since various behavioral movement patterns are likely to be valid within different, unique ranges of spatial and temporal scales (e.g., instantaneous, diurnal, or seasonal) with the corresponding spatial extents, a cross-scale approach is needed for accurate classification of behaviors expressed in movement. Here, we introduce a methodology for the characterization and classification of behavioral movement data that relies on computing and analyzing movement features jointly in both the spatial and temporal domains. The proposed methodology consists of three stages. In the first stage, focusing on the spatial domain, the underlying movement space is partitioned into several zonings that correspond to different spatial scales, and features related to movement are computed for each partitioning level. In the second stage, concentrating on the temporal domain, several movement parameters are computed from trajectories across a series of temporal windows of increasing sizes, yielding another set of input features for the classification. For both the spatial and the temporal domains, the "reliable scale" is determined by an automated procedure. This is the scale at which the best classification accuracy is achieved, using only spatial or temporal input features, respectively. The third stage takes the measures from the spatial and temporal domains of movement, computed at the corresponding reliable scales, as input features for behavioral classification. With a feature selection procedure, the most relevant features contributing to known behavioral states are extracted and used to learn a classification model. The potential of the proposed approach is demonstrated on a dataset of adult zebrafish (*Danio rerio*) swimming movements in testing tanks, following exposure to different drug treatments. Our results show that behavioral classification accuracy greatly increases when firstly cross-scale analysis is used to determine the best analysis scale, and secondly input features from both the spatial and the temporal domains of movement are combined. These results may have several important practical applications, including drug screening for biomedical research.

Keywords: cross-scale movement analysis, spatial scaling, temporal scaling, movement parameters, machine learning, zebrafish swimming, behavioral pharmacology, drug screening

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1 Introduction

Understanding behavioral dynamics of moving objects is becoming the focus of many researchers in various fields of GIScience. Discovering latent information about behaviors of objects from raw movement data, typically comprised of a series of time-stamped fixes, needs more sophisticated approaches to improve characterizing different behavioral states. Fix-based measures, further referred to as movement parameters (MPs, e.g., speed, acceleration, or turning angle), have been used to assess the key characteristics describing the movement of objects [5, 6]. However, the primary interest of studying MPs in movement analysis is in characterizing different behavioral states and investigate how they change over time [30]. Since movement occurs in space and time, exploration of both the underlying spatial extent and the relevant temporal characteristics of movement processes are needed to understand the fundamental behavioral mechanisms. Additionally, the scale at which the data is analyzed is an important determinant for behavioral characterization of movement data. Since different behavioral patterns and processes are likely to be valid within their own unique range of spatial and temporal scales, understanding the functional hierarchy underlying movement processes necessitates investigation of movement mechanisms and patterns across multiple spatiotemporal scales [26].

On the other hand, from the extensive literature in this field, "it is clear that scale is a problematic issue in many sciences, notably those that study phenomena embedded in space and time" [12]. In areas outside movement analysis, it has been demonstrated that the understanding of observed phenomena requires the elucidation of mechanisms intertwining pattern and scale, as well as exploring how the information is transformed from fine scales to coarse scales, and back [24]. In movement analysis, scale is both a spatial and a temporal property, and these two properties may reflect the trajectory data or the space of the movement process. The spatial separation of observation points along a movement trajectory affects the temporal sampling granularity, and vice versa [22]. However (as the review of the pertinent literature in the following section will show), there is little evidence of cross-scale analysis of movement data, compared to an abundance of studies restricted to single scales. One reason for this knowledge gap may be because data complexity can be expected to increase significantly when multiple scales are introduced. Additionally, interpretation and evaluation of patterns emerging at different scales need considerable discussions, and may benefit from engagement between the developers of the analysis methods and the domain experts.

As a definition, cross-scale analysis of movement data refers to methods and algorithms capable of investigating the relationships between patterns and processes that occur at multiple spatial and/or temporal scales, respectively. The main prerequisite for such an analysis is the availability of highly granular data, which is facilitated through recent advances in tracking technologies, such as global positioning system (GPS) or indoor video-tracking systems. As these technologies are becoming less expensive, large data volumes can capture the movement trajectories of many individual objects over long time periods at fine temporal granularities. However, we posit that in order to extract behaviors from such high-resolution data, a cross-scale analysis approach is needed. Alternatively, confining the analysis scale to the original temporal granularity of movement data forces all data analysis to be scale-specific as well [22], which can be too constraining. Importantly, the movement processes that comprise a behavioral state emerge from cross-scale interactions generating these behaviors, and cannot be predicted based on observations at single or multiple independent scales. Therefore, cross-scale exploration of patterns and relationships in movement analysis is needed in order to yield cross-scale behavioral clues.

This article makes contributions in two areas. We improve *cross-scale analysis* of movement behavior by proposing a comprehensive methodology based for integrating measures from coordinated spatial and temporal granularities to yield a holistic picture of movement behavior at different levels of scale. Furthermore, we demonstrate the use of *machine learning* (ML) to aid cross-scale movement analysis, in response to the need for efficient methods to capture cross-scale effects represented in movement data. We provide a procedure that uses ML to establish the spatial and temporal scales at which movement parameters can be reliably measured and the classification performance is optimized. Based on the learned patterns, the proposed approach can be useful for classifying unknown trajectories into user-defined movement classes (based on training data with known labels).

As a case study, developed in collaboration with a neuropharmacology research group, the potential of the proposed methodology is demonstrated on a video-tracking dataset of movement of adult zebrafish (*Danio rerio)*, a rapidly emerging novel animal model for translational biomedical research, drug screening and therapeutic target detection [2,7,35]. In our training dataset, the fish were exposed to different drug classes, composed of anxiogenic (stress/anxiety-inducing) and anxiolytic (stress/anxiety reducing) drug treatments. Based on the nature of these drug treatments, the fish display a distinct set of movement variations, traversing different parts of the tank, and ultimately representing different empirically established behavioral states [2,3]. We aim to delineate these differences by first dividing the tank arena into several spatial zones, and then by computing movement parameters (e.g., speed, acceleration, turning angle, meandering, sinuosity) at different temporal windows. Therefore, since the applied measures are calculated across different spatial and temporal scales, the extracted feature sets can uniquely describe the behavioral patterns of the zebrafish.

The remainder of this article is organized as follows: Section 2 examines the state-of-the-art of movement pattern analysis using cross-scale methods (e.g., in GIScience, ecology and neuropharmacology). Furthermore, a review of studies using ML to aid cross-scale movement data analysis is included in this section. Section 3 provides a detailed overview of the analysis approach employed in this study. The case study on zebrafish data is explained in Section 4, and the corresponding results are presented in Section 5. Section 6 provides the interpretation and discussion of the findings of this study, and Section 7 offers concluding remarks and suggestions for future research.

2 State-of-the-art

In the context of this paper, we restrict our review to previous research in two different areas: (1) cross-scale analysis of movement data and (2) machine learning methods in movement analysis.

2.1 Cross-scale analysis of movement data

While the literature on cross-scale analyses of movement data is sparse, their importance has been recognized in an increasing number of studies. In animal ecology, for example, methods for inferring behaviors and changes in behaviors within the movement trajectories of animals have become increasingly popular in recent years. Fryxell et al. [10] review several studies investigating animal movement at three different spatio-temporal scales (coarse-scale, intermediate-scale, and fine-scale). Postlethwaite et al. [30] discuss popular examples that are capable of addressing scale issues in animal movement data, including Markov models, Bayesian fitting techniques, and wavelet-based approaches. However, most such cross-scale studies focus on an ecological perspective, restricted to specific data sources and to answering specific research questions.

The work by Laube and Purves [22] is probably the most relevant research in GIScience for developing a methodological perspective of cross-scale movement analysis. They proposed a general approach for investigating to what degree movement parameters such as speed, sinuosity, or turning angle do vary when derived at variable temporal scales. However, in cases when spatial scaling is also critical, such an approach may not be ideal due to its exclusive focus on the temporal domain. Dodge et al. [5] also used features captured at global and local levels of trajectories for automatic movement mode detection. Global features relate to the level of the entire trajectory, while local ones are at the level of segments of homogeneous movement characteristics. Recently, Postlethwaite et al. [30] introduced a new multi-scale measure, the multi-scale straightness index (MSSI), for analyzing animal movement data. MSSI is used for classifying sequential sub-sections of individual trajectories into different behavioral states and for evaluating how behavior (expressed within trajectories) varies over different temporal scales. In neuroscience, multi-scale analysis of movement data has also attracted the attention of researchers, especially in the field of drug discovery. For example, Kafkafi et al. [21] used path texture as a behavioral measure for characterizing path curvature of mice moving in an open-field arena across several spatial scales. They showed how this measure can be used for distinguishing different drug treatments within the same drug type (i.e., serotonin agonists). The same group [20] in another study used a data mining approach called *pattern array* (PA) to analyze mouse open-field behavior and characterize the psychopharmacological effects of three drug classes: psychomotor stimulant, opioid, and psychotomimetic.

The review of the above-mentioned methods reveals the strong potential of cross-scale analysis of movement data. However, there is still a need for a more comprehensive cross-scale methodology that can simultaneously incorporate both the spatial and temporal dimensions of movement data, applicable to different domains of movement research. Thus, in Sections 3 and 4, we show that in addition to varying the temporal scale, partitioning the underlying space also facilitates the extraction of relevant patterns.

2.2 Machine learning (ML) in movement analysis

In this study, we explore ML and its capacity to aid cross-scale movement analysis. Traditional movement pattern recognition algorithms cope well with large data volumes. However, many studies that employ such deterministic techniques are based on data sources limited to specific scales (and, therefore, less generalizable for other applications). Thus, more sophisticated approaches are needed in response to the needs of movement behavior analysis, and ML can offer a potential avenue for that, as a review of the pertinent literature shows. Examples range from using Bayesian networks and decision trees to study the migration of birds [14], to the use of support vector machines (SVMs) for categorizing behaviors of tracked lab animals such as rats [9], movement of cows [25], and analysis of the movement of caribou using hidden Markov models (HMMs) [8]. Hu et al. [17] used self-organizing maps (SOMs) for learning the pattern of motion trajectories among pedestrians and making predictions about vehicle movement in transportation studies. Torrens et al. [36] used ML for benchmarking an agent-based simulated pedestrian's relative behavior in indoor and outdoor scenes. In biology, ML methods such as SVM have been used for trajectory segmentation to identify distinct types of human adenovirus motion in host cells [16], classifying trajectories of moving keratocyte cells [32], and for automated recognition of movement patterns using gait data [1].

Here, we apply two functionalities of ML for cross-scale movement analysis. A feature selection procedure is used to determine the most relevant movement variables with input parameters captured at different temporal and spatial scales and then, based on the selected features, a classification model is built using SVM to classify the trajectory data into user-defined data classes.

3 Methodology

"Scale" has many meanings, but in GIS two are of greatest significance: resolution and extent [12]. For movement data, the intertwining notions of spatial and temporal scales make the interpretation of scale even more complex. Focusing on the quantitative representation and classification of movement, we explore "scale" both in terms of "temporal resolution/granularity" and the "spatial extent."

The methodology proposed here consists of three stages (Figure 1). First, for scaling in the spatial domain, the underlying movement space is partitioned into several zones. This procedure is automated to decide on the extent of the partitioned zones at different levels. For each moving object, several parameters (corresponding to different zones) can be calculated, and considered as input features in the classification model. In the second stage, values of movement parameters are calculated across different temporal window sizes, based on the approach proposed by Laube et al. [22]. In both these stages, the set of extracted variables (spatial or temporal, respectively) are evaluated based on their contribution to the improvement of classification accuracy. At the same time, the "reliable analysis scale" (i.e., the scale range at which movement parameters can be reasonably and reliably calculated) is determined to improve the accuracy and precision of the prediction models. In the third stage, measures from the spatial and temporal domains of movement are used as input features for classification. With a feature selection procedure, the most relevant features contributing to known behavioral states are extracted and used to learn a classification model.

We will now introduce the three stages of the methodology in the following three subsections. The overall flow of the methodology is summarized in Figure 1 (in further text, we use Roman numerals to denote the three stages, and Arabic numerals to denote the individual steps within each stage).

3.1 Stage I: Spatial scaling

In Step I.1 of our proposed methodology, subdivision of the underlying spatial domain into different zones, and changing their size, are used to investigate spatial scaling. The resulting zones after spatial tessellation are considered as the fundamental extent of the spatial domain. The impact of aggregation and zoning in the analysis of aggregate spatial data has been already well-addressed, through the modifiable areal unit problem (MAUP) [27,34]. The two components of the MAUP include scale (level of aggregation) and zoning (level of partitioning). While the first one concerns statistical inferences generated by the same data aggregated to different spatial resolutions, the latter refers to variations in the results due to alternative partitionings (zonings) at the same spatial scale. The procedure employed here for addressing spatial scaling is related to the MAUP to some degree, but the main difference lies in the way that the different zones are aggregated. The zonings used in this study are biologically-driven and there is also not a strict hierarchy between the levels as in MAUP. In other words, the partitioning of the movement space is constructed such that it biologically makes sense; this may also affect the aggregation levels, which may not follow a strict hierarchy, as we will show in the case study of this article. We will return to the MAUP in Section 6.

As shown in Step I.1 in Figure 1, we focus on three hierarchical levels of subdivision which correspond to different spatial scales: "micro" is confined to the scale of finely grained zones; "meso" points to the level of aggregated micro-zones; and "macro" refers to the coarsest possible spatial extent. First, preliminary micro-level zones are specified in discussion with domain experts to establish a meaningful fundamental partitioning of space. Then these zones are aggregated in order to form new zones that extend over a wider spatial scope, first at the meso, then at the macro scale. Such aggregation is warranted by the need for evaluating the patterns mined at different spatial scales, as well as by partitioning schemes that are meaningful from the perspective of the behaviors of the moving object under study.

In Step I.2, different measures are computed within each zone, and considered as input features for the classification. Examples of these measures include: time spent in different zones; characteristics of movement parameters within zones (e.g., descriptive statistics of MP values for each zone); contextual information linked to the zones (e.g., certain zones might be more prone to specific behaviors or they might be related to particular food resources); and frequent transitions between zones. In this study, for instance, the duration of time spent in different zones is calculated to determine the movement episodes within which the object is more stationary or more mobile, respectively. Cross-scale analysis based on different spatial partitioning is included in this step. When the spatial domain is decomposed into several hierarchically nested regions, this approach yields multiple partitioning

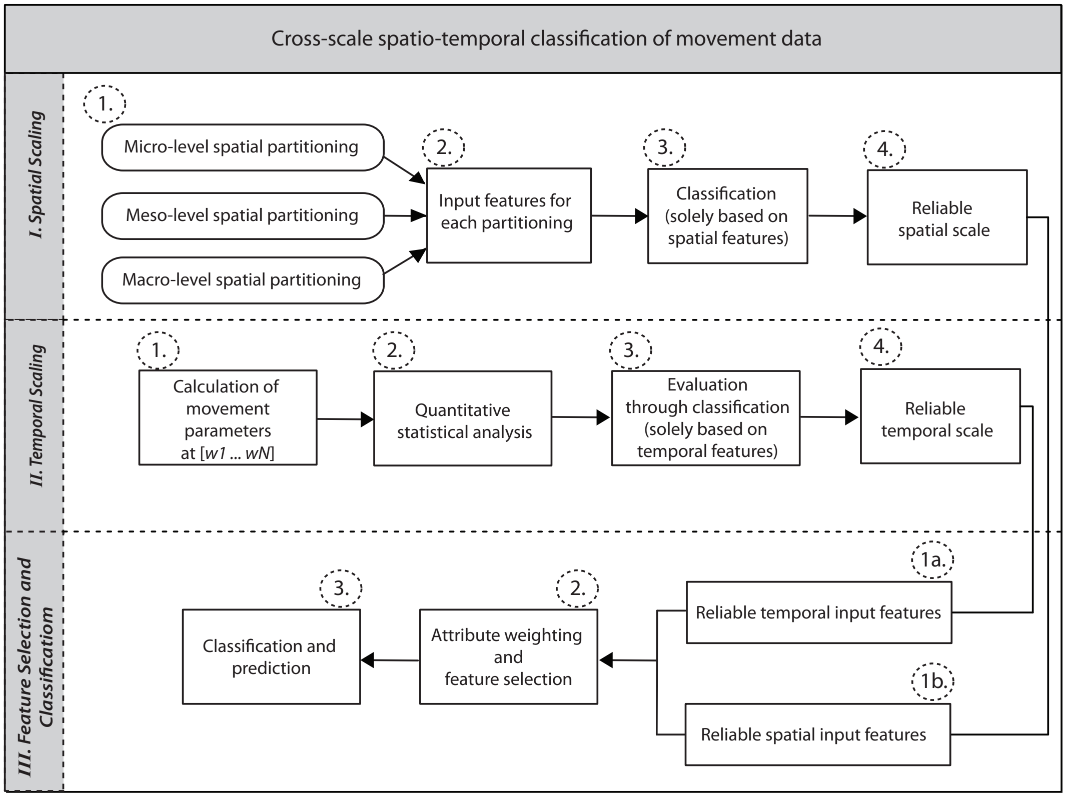

Figure 1: Overview of applied approach for cross-scale analysis of movement data.

schemes at multiple scales and different extents. Collectively, this enables analyzing the patterns of variation of computed measures across spatial scales and different partitions, contributing to choosing the "reliable spatial scale" (described in Step I.4).

In Step I.3, input features are developed for each trajectory by selecting desired measures, subsequently imported to the classification model. In this step, only spatial features are considered, such as the examples given in Step I.2.

In Step I.4, the reliable spatial scale is determined automatically. The reliable spatial scale is obtained as the scale at which the highest classification performance is achieved when only spatial features are employed in the classification. For this purpose, the classification performance of different partitioning schemes in Step I.3 is evaluated based on some performance measures. For these measures, in addition to the classification accuracy and class recall values, we also use Cohen's kappa coefficient [4] as a measure that is more robust than the percentage values reported from classification models. The method used to determine the reliable scale requires being able to flexibly modify the spatial partitioning, thus favoring zone partitioning schemes that can be easily varied, such as a scheme based on a percentage area per zone. Importantly, this allows researchers to quickly evaluate various spatial scaling arrangements as related to their research question.

3.2 Stage II: Temporal scaling

In Step II.1, a series of moving temporal windows (w_i) of different sizes are used within which the movement parameters are calculated. For this, the method of Laube et al. [22] appears to deliver meaningful results. By varying the temporal width of w_i, values of computed movement parameters can be examined over a wide range of scales (see [22] for details). To define the useful range of window sizes, we suggest using the temporal characteristics of the behaviors to be mined in the movement analysis process. For example, here the minimum window size is set to the smallest possible interval at which movement parameter can be computed (i.e., using 3 consecutive points), and the maximum window size is set to the duration of particular movement patterns that comprise basic behaviors performed by the moving object under study. For instance, in our zebrafish case study, the original sampling interval of 30fps yields a minimum window size of 0.1s, while the maximum window size was set to 7.5 s, corresponding to the maximum duration of an "erratic movement" (see details in Section 4). Note that if larger window sizes are used, some of these behaviors might be missed. For example, simply calculating the movement parameters only on one specific scale over the entire trajectory misses many important "micro-movement" features that hold predictive value for behavioral research [5]. Since different mechanisms corresponding to various behaviors in the movement process are important at different scales, variation of movement parameters can be used to exploit relevant cross-scale behavioral patterns [11, 28, 29].

The MPs used in our zebrafish case study include speed, acceleration, turning angle, meandering, and sinuosity, computed in the 2-D space (see Section 4). Meandering and sinuosity are both indicators of straightness or curvature of a path (or, in our case, a trajectory of a zebrafish swimming). Meandering represents the ratio of the turning angle to the bee line (i.e., the shortest distance between starting and ending points), while sinuosity is the ratio of the actual distance traveled along the track to the bee line. The influence of temporal scale for each of these parameters is explored by changing the size of the temporal window w. The values of the movement parameters are calculated for every fix at all scales, in a segment where $w/2$ fixes exist before and after the sample point of interest [22].

In Step II.2, boxplots of the mean values of the movement parameters for all trajectories are investigated to assess if any significant patterns can be observed. The results of this step are considered as an input to determining the reliable temporal scale later in Step II.4. Importantly, as boxplots assess the signal-to-noise ratio, we expect that after a certain threshold (for the size of the temporal window), the variation of mean values of movement parameters can stabilize, and this is also where the signal-to-noise ratio may be expected to level off at its highest value.

Step II.3 examines whether the variation represented in the boxplots can define the reliable temporal scale. For this purpose, the same classification procedure (as in the spatial scaling stage) was employed, but this time relying only on the developed temporal features. Input features for this classification may include statistical variables of movement parameters (e.g., the global minimum, maximum, mean, and standard deviation of a particular movement parameter over the entire trajectory). For each trajectory, these values are first computed within several temporal windows, and then separately input to a classification procedure. The resulting corresponding measures of classification performance allow comparing the ability of different temporal scales to distinguish between behaviors.

Finally, Step II.4 takes the outputs of the two previous steps. The reliable temporal scale used in Stage III is selected by comparison of the variation exhibited in the boxplots

(Step II.2) and the resulting classification performance measures (Step II.3). As reliable temporal scale, we choose the first temporal window size that is most similar in its variation of MP values to the variation of the largest window size, and where the best classification performance is achieved.

3.3 Stage III: Feature selection and classification of trajectories

Step III.1: After the reliable spatial and temporal scales have been separately identified using cross-scale analysis approaches (in the previous stages I and II, respectively), the corresponding feature sets extracted at these specific scales are used jointly for the final feature selection and classification stage.

Step III.2 applies a two-phase feature weighting/selection approach. Briefly, for all the input features, a variable ranking algorithm (e.g., SVM weighting) is first used to rank the features in the order of their contribution to correctly assigning class labels [15, 31], to determine the significance of either the spatial or the temporal features and their contribution to the behavioral states. Ranking allows filtering-out of irrelevant input features by a user-defined threshold (e.g., maximal number of features used, or minimum necessary weight). Thus, in the remainder of the classification process only a selected number of features are applied. In the second phase of Step III.2, a feature selection process is employed to determine the ultimately relevant features best describing the behavioral mechanisms. For example, in the case study described in Section 4, we used an evolutionary feature selection process using genetic algorithms (GAs) in conjunction with SVMs.

Finally, in Step III.3 the model built in the preceding stages and steps is used to predict the behavioral labels (e.g., drug treatment classification, in our case study) of unlabeled trajectory data.

4 Case study

In order to demonstrate the applicability of the proposed methodology, we used a case study consisting of a series of experimental evaluations, using a dataset of zebrafish movement data collected for a different behavioral project [3].

Developing expedient analysis methods in neurobehavioral research represents a significant contribution to a rapidly emerging field in psychopharmacology drug research [19, 23, 38]. Zebrafish offer several methodological and practical advantages over traditional rodent models, and further development of these techniques is invaluable for pharmaceutical research [3]. The behavioral data for this study was generated by video tracking software[1], which analyzes videos of zebrafish swimming activity at 30 frames per second, rendering them feasible for cross-scale analysis. In these psychopharmacological trials, experimental zebrafish were treated with psychoactive drugs with known neural targets and action (Table 1; for more information on the specific drug treatments and zebrafish trials, see [2, 3, 7, 13, 35]).

The testing tank type used was a 1.5-L trapezoidal tank with the following dimensions: 15.2cm height $\times$ 27.9cm top $\times$ 22.5cm bottom $\times$ 7.1cm width. The tank is deliberately designed to be rather narrow (only 7.1cm), such that video tracking can take place from

[1]Noldus EthoVision XT 8.5; Noldus IT, The Netherlands

Treatment Class	Individual Trajectories*	Treatments
Anxiogenic	75	Alarm Pheromone, Caffeine, Morphine Withdrawal
Anxiolytic	107	Fluoxetine, Nicotine, Ethanol, Morphine
Control	227	Wild-Type (short-fin) untreated, age-matched zebrafish

* Each animal was analyzed once, and each trajectory represents an individual zebrafish

Table 1: Description of dataset.

the side view, that is, in 2-D, neglecting the narrow third dimension. Figure 2 provides examples of pseudo 3-D temporal reconstructions of raw trajectories, similar to a space-time cube representation, to illustrate the data used in our study. The 2-D trapezoidal cross-section of the side view of the tank can be clearly seen. Once again, it should be noted that the actual tracking data used are 2-D (x,y) coordinates and the space-time cube reconstructions are only shown to give a better picture of zebrafish movement. Thus, it becomes visible how the differences in mechanisms of action between the three treatment classes can be detected qualitatively. As we will demonstrate further, these differences in manifested behavior can be exploited in a classification strategy.

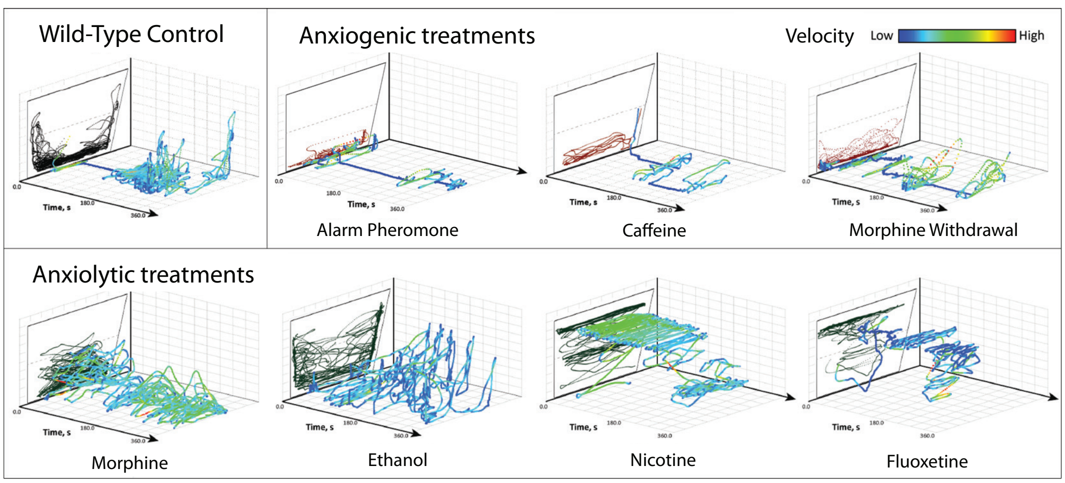

Figure 2: Space-time cube temporal reconstructions of zebrafish swim paths treated with different drugs (adapted from [3]). Note also the projection to the 2-D trapezoidal side view of the test tank, which is the view that is used for data capture by video tracking, as well as for spatial partitioning (cf. Figure 3).

The present study had the ultimate goal of developing an effective behavioral analysis tool that discriminates (and may eventually predict) drugs with similar mechanisms of action based solely on the evoked locomotor activity. The proposed methodology was first employed to comprehensively describe the zebrafish behavior through assigning unique feature sets to different classes of drug treatments in relation to tank zones (e.g., during high-stress states caused by anxiogenic drugs, zebrafish tend to stay along the bottom and freeze for extended times, as shown in Figure 2; see [7] for more details on the effects of pharmacological manipulations on behavioral phenotypes of zebrafish). We next built a ML model of fish behavior using previously classified trajectories in order to predict the drug treatments of "blind" zebrafish trajectories (with either known or novel psychoactive compounds used in the screening assays of pharmaceutical research). As restricting the analysis to specific predetermined temporal and/or spatial scale does not achieve these goals [20], the dynamic approach employed here may represent a solution. For example, the difference between a zebrafish swimming rapidly in very tightly intertwined circles or in large swooping circles throughout the arena may represent the difference between seizure-like activity and expanded exploratory activity (indicative of an anxiolytic, stress-reducing drug action). Each of these behaviors requires careful attention to the spatial and temporal scale used to calculate descriptive variables of the trajectory.

Thus, the cross-scale analysis approach described here is proposed to exploit the increasing volume of potentially valuable movement data collected in contemporary zebrafish behavioral studies (and, in fact, in other animal neurobehavioral studies as well).

Manipulations that comprise two primary classes were used in this study: stress-inducing drugs (*Anxiogenic*), including Alarm Pheromone, Caffeine, Morphine Withdrawal; and stress-reducing drugs (*Anxiolytic*), including Fluoxetine, Nicotine, Ethanol, Morphine. The third treatment class included the wild-type, untreated *Control* zebrafish. Increased anxiety caused by the anxiogenic drugs can be seen through some behavioral parameters in the movement: e.g., longer latency to enter the upper half of the tank, reduced time spent in the top, as well as increased erratic movements and freezing. In contrast, reduced anxiety in this test is accompanied by increased exploration of the tank with reduced freezing and fewer erratic bouts [3,7]. The description of the dataset used and the numbers of trajectories is given in Table 1. After pre-treatment, zebrafish were placed individually in a testing tank maximally filled with aquarium treated water, and the 6-min novel tank test trial was recorded with HD USB web-cameras (see [3] for details).

The methodology introduced in Section 3 was applied as follows:

Stage I In Stage I, in order to partition the underlying spatial domain of the fish movement in the tank arena, a three-step spatial partitioning procedure was applied (the tank arena is the side view of the tank, as already mentioned in Figure 2): In the first step, the tank arena was partitioned into 9 zones, including 4 corner zones, 4 edge zones and 1 middle zone (Figure 3a). The areas of all corner zones were set to be the same with the 2.5cm edge margin. This resulted in a ratio of the area of surrounding zones (all corners and edges) to the whole arena of $\sim$54% (note that varying the edge margins changes the percentage area values). This 9-zone partition was designed because so far the effects of corner and edge zones had been hypothesized to exist but have not yet been studied in zebrafish research. In the second step of this procedure, a 3-zone subdivision was applied. The 3 top zones from the 9-zone subdivision were aggregated to one top zone, and the same aggregation was then applied to the 3 middle and 3 bottom zones, respectively (Figure 3b). Finally, a 2-zone subdivision was utilized based on the conventional approach in zebrafish research to divide the tank arena into a top and a bottom zones using the origin coordinates (0,0) of the tank (Figure 3c). Our cross-scale partitioning approach forgoes the use of "traditional" or "classic" zone partitioning schemes (represented in Figure 3c), thus avoiding a priori attributions biasing the interpretation of experimental results. Additionally, our method allows for rapidly changing the zones by entering a percentage of area to calculate partitions before processing the experimental data. In this case study, the only variable generated as an input feature for the subsequent classification stage was the time spent (i.e., the duration) in each zone, calculated per trajectory and per subdivision scheme. The decision to use this variable was made after preliminary feature selection and classification experiments. Although the variable measures a temporal quantity (duration), we term it a spatial variable since it is the result of spatial scaling, calculated for each spatial zone.

Stage II In Stage II, the values of movement parameters for each fix of a trajectory were calculated at different temporal window sizes. The five selected movement parameters were then calculated for seven temporal scales (w = 0.1, 0.3, 0.5, 1, 2.5, 5, or 7.5s). Varying the size of window in this range is important, and depends on the amount of time required for a specific "behavioral event" (e.g., erratic movement) to occur. Specifically, if the temporal window is too small, the larger behavioral events are missed from analysis. Likewise, if it is too large, behavioral events blend out into an "average" locomotor state. The value of exploring multiple windows is to tease out the window size that allows us to both comprise and distinguish the distinct behavioral states in zebrafish.

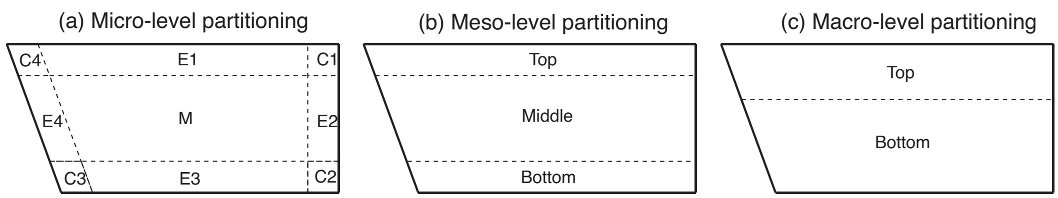

Figure 3: Zebrafish tank arena partitioning at three levels: (a) Micro-level 9-zone subdivision includes 4 corner zones (C1-C4), 4 edge zones (E1-E4) and 1 middle zone (M). (b) Meso-level 3-zone subdivision includes top, middle, and bottom zones. (c) Macro-level 2-zone subdivision includes top and bottom zones.

Stage III In Stage III, we first applied an SVM weighting function (with the complexity weighting factor of 0) for ranking the input features. The feature weights represent the coefficients of a hyperplane separating the classes by an SVM classifier [31]. This step was performed to remove features that are highly correlated or have similar values within classes, and thus do not contribute significantly to discriminating between treatment classes.

Subsequent learning and classification stage applied a supervised, evolutionary feature-selection algorithm using GAs in conjunction with SVMs [18,37]. The combination of GAs and SVMs for feature selection was chosen due to their better performance, compared to other existing methods. We used a radial basis function (RBF, [33]) for the SVM kernel with the following parameter settings: $C = 20$, which is an offset parameter imposing a trade-off between training error and generalization performance of SVM classifier and $\gamma = 0.001$, which is an exponent factor in the RBF function. These settings were the same when the classification was run solely based on spatial features (step I.3) and temporal features (step II.3). The reported results are based on a 10-fold cross-validation in each SVM learning phase and with the following parameter settings for GA:

- Population size: 25

- Number of generations: 100
- Probability of crossover: 0.8
- Probability of mutation: 1 / (number of features) for each individual

Using a feature selection process, a set of movement features was extracted, including a combination of movement parameters and time spent in different zones, which yielded dominant SVM weights for labeling the drug classes. Finding spatial and temporal features of movement that can best differentiate drug classes was the intended outcome of this step. A classification model was then built to classify the labeled data based on selected features.

The calculation of movement parameters was implemented in MATLAB (R2010b), while ML procedures (including feature selection and classification) were implemented in RapidMiner 5, an open-source machine learning and data mining package[2]. Three-dimensional trajectory reconstructions were also generated in RapidMiner 5 (see [3] for details).

5 Results

5.1 Spatial scaling through arena partitioning

The times spent in different zones (based on the 3-arena partitioning procedures) were calculated for all trajectories of the 3-treatment cohorts (Step I.1 in Figure 1). Averaged values for each of these classes are illustrated in Figure 4. While these "maps" only show the mean values over all trajectories within a treatment class, we can already see some patterns in the distribution over the zones. For example, while the 2-zone subdivision shows little difference between the treatment classes, the other subdivision schemes exhibit more distinct treatment effects.

The times spent in each zone were then used as input features for the subsequent classification in Step I.2. Note that depending on the arena partitioning scheme used, the number of input features will differ, commensurate with the number of zones (i.e., 2, 3, or 9). For the classification process (Step I.3), we used an SVM classifier. Table 2 shows the classification performance achieved by the 3 subdivision schemes of the tank arena, including the precision and recall per class, as well as the overall classification accuracy and kappa values per subdivision. As already suggested by Figure 4, the 2-zone subdivision performs weakest, while there was a steady increase in the values of overall classification accuracy and kappa values as the number of zones increases (Table 2). Thus, for the given options of partitioning schemes, the 9-zone subdivision can be selected as the "reliable spatial scale" (Step I.4), markedly improving drug characterization based on zebrafish behavioral responses.

5.2 Temporal scaling through calculation of movement parameters at different windows

For all trajectories of the three treatment classes, values of movement parameters at the temporal windows stated in Section 4 were computed in Step II.1 (Figure 1). Boxplots were generated to characterize the variation of mean values per trajectory of three movement parameters for all trajectories of a particular treatment class, calculated at the different

[2]Rapid-I, GmbH, http://rapid-i.org

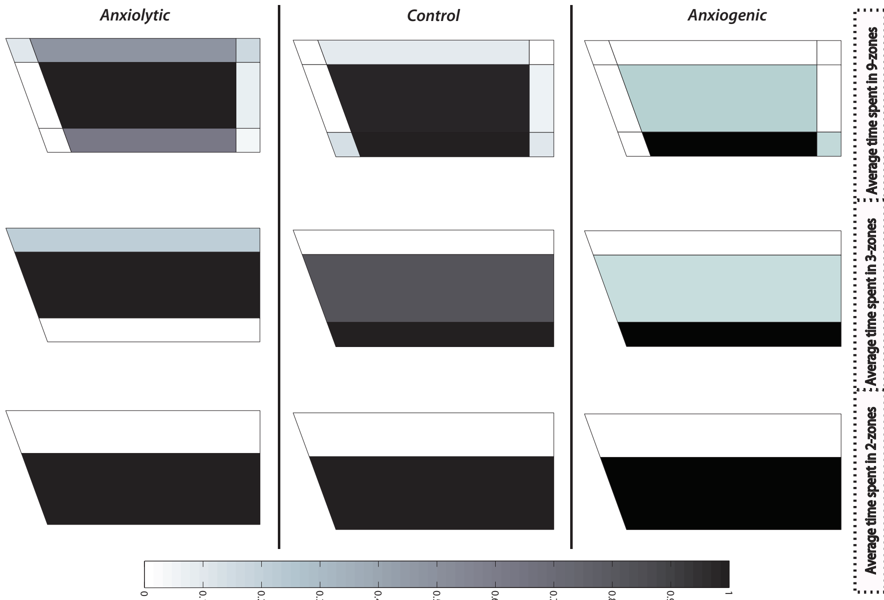

Figure 4: Averaged values of time spent in different zones for anxiolytic, control, and anxiogenic classes. The color scheme from 0 to 1 indicates the overall duration of experimental psychopharmacological zebrafish trials. Since each trial possessed slight time differences (±1s), they are scaled to range of [0–1] (0–360s) in order to be comparable to each other.

temporal windows (Step II.2). Figure 5 shows the variation of speed, acceleration, and sinuosity for the three treatment classes and 7 temporal windows. It is worth noting that the remaining movement parameters (i.e., turning angle or meandering) showed no clear patterns in the evolution of boxplots, and were therefore no longer shown in these graphs.

The main objective of using boxplots here was to investigate the signal-to-noise ratio in order to subsequently select the appropriate temporal window in which movement parameters can be reliably computed. There was a generally steady increase in the magnitude of acceleration and sinuosity values; whereas the speed values are decreasing as the window size increases. The revealed patterns in the boxplots for the anxiolytic and control classes were quite similar, indicating the need for using more additional features (e.g., spatial scaling parameters) to help discriminate these two classes. In contrast, a more unique pattern can be observed for the anxiogenic treatment class.

As was already mentioned, the largest window size (i.e., 7.5s) was defined based on the approximate time needed for a full behavioral event (e.g., a so-called startle movement) to take place. It is clear, however, that some events may take less time. Therefore, we sought to find a window size that is smaller than the 7.5s window, yet most similar in terms of the variation of the movement parameters. Thus, the intention was to capture the more fine-grained behaviors, while at the same time removing potential noise in the data. For this purpose, we examined the boxplots for the different movement parameters. While for sinuosity, both the median and interquartile range show a steady or even accelerating

Spatial scaling procedure	Predicted drug class	Observed drug class			Class precision	Classification accuracy	Kappa coeff.
		Control	Anxiogenic	Anxiolytic			
Subdivision: 2-zones	Control	168	24	58	67.20%		
	Anxiogenic	46	50	11	46.73%		
	Anxiolytic	13	1	38	73.08%		
	Class recall	74.01%	66.67%	35.51%		62.59%	0.354
Subdivision: 3-zones	Control	187	28	36	74.50%		
	Anxiogenic	25	43	9	55.84%		
	Anxiolytic	15	4	62	76.54%		
	Class recall	82.38%	57.33%	57.94%		71.39%	0.501
Subdivision: 9-zones	Control	211	16	28	82.75%		
	Anxiogenic	13	59	4	77.63%		
	Anxiolytic	3	0	75	96.15%		
	Class recall	92.95%	78.67%	70.09%		84.35%	0.725

Table 2: Classification results based solely on the time spent in zones of different partitioning levels (e.g., 2-zones, 3-zones, 9-zones).

increase with increasing scale, the values for speed (particularly in the anxiogenic class) and acceleration (in all treatment classes) start to stabilize. That is, at the scale of 5s the median and interquartile range start approximating the window size of 7.5s.

These observations suggest a way to optimize the reliable temporal window size (w) selection. Since it was important to keep the size of the window as small as possible (in order not to miss underlying fine-grained behaviors), we selected 5s as the window size for the final feature selection and classification process. To evaluate this assumption and see whether boxplots may help in the identification of the reliable temporal window, identical classification analyses were conducted (Step II.3), where no spatial subdivision is considered and input features comprised only descriptive statistics of movement parameters (based on the variation of the temporal window). The corresponding results are shown in Table 3. As expected, none of the window sizes resulted in a better classification result than the 5s, indicating the validity of the cross-scale approach employed here to select the most reliable temporal window. While there is an increase in the performance measures up to window size of 5s, the results decline for window size of 7.5s. Furthermore, the best classification performance from temporal scaling (kappa = 0.605; Table 3) was lower than the best performance obtained from spatial partitioning (kappa = 0.725; Table 2). This suggests that the underlying behavioral mechanisms are intertwined, and that temporal scaling alone does not suffice to generate accurate behavioral classification results.

5.3 Feature selection and classification of movement data

For each trajectory, we applied two sets of input features for the classification process. From the results of Section 5.1, times spent within the 9-zone subdivision profile were used (Step III.1a). From the results of Section 5.2, four statistical descriptors of all five movement parameters calculated at varying temporal window sizes were used (Step III.1b). Thus, for each trajectory, a total of 29 input features were considered for the subsequent feature

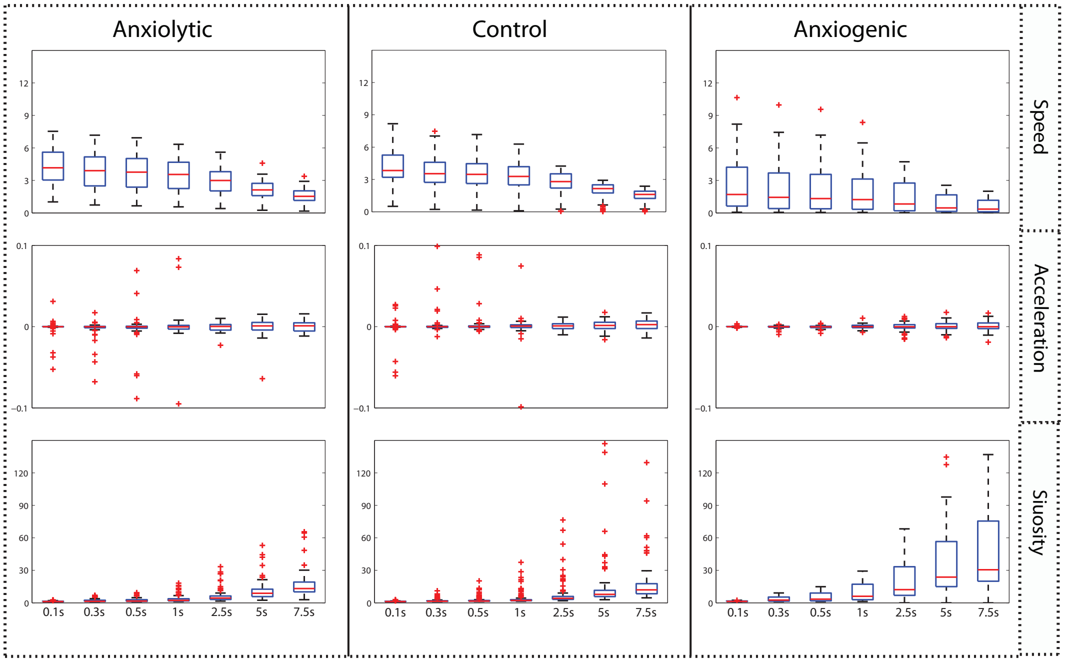

Figure 5: Boxplots of variation of mean values of three movement parameters (speed, acceleration, and sinuosity) of all trajectories for three classes of anxiolytic, control, and anxiogenic treatments, calculated at temporal windows of 0.1, 0.3, 0.5, 1, 2.5, 5, and 7.5s.

selection and classification process. As already described in Section 3, before the classification process, an SVM weighting function was used to select the most predominant input features (Step III.2). This was achieved by building a classification model iteratively in order to remove features that are highly correlated or have similar values within classes, and thus do not contribute much to discriminating between treatment classes.

The results of the SVM weighting function give an indication of the significance of different features based on their weights; they are reported in Figure 6. The top 20 features were chosen based on their resulting weights. The meanings of these features are shown in Table 4. The features indicating the time spent in a particular zone (e.g., DurC1-4, DurE1-4, DurM) are spatial features, while the remainder are temporal features (MeanderStd, TurnMin, etc). The reason for selecting this number of features is that the obtained results are far off if all input features are used instead of selected 20 features. Furthermore, from an ML point of view, there should be enough features to build and test the classification model, and at the same time avoid noise and/or correlated features. This is achieved through an iterative process where different numbers of features are tested in order to obtain optimal classification results. The designated features are imported in the classification process by applying an evolutionary feature selection using GA in conjunction with an SVM learning model, where the feature selection procedure uses the delivered classification accuracy as its fitness function. Representative corresponding results are shown in Table 5.

As shown in Table 5, various arena partitioning strategies as well as other temporal window sizes were tested through the same feature selection and classification procedure.

Temporal scaling procedure	Predicted drug class	Observed drug class: Control	Anxiogenic	Anxiolytic	Class precision	Classification accuracy	Kappa coeff.
Window size: 0.1s	Control	227	40	47	72.29%		
	Anxiogenic	0	35	0	100.00%		
	Anxiolytic	0	0	60	100.00%		
	Class recall	100.00%	46.67%	56.07%		78.73%	0.591
Window size: 1s	Control	221	40	45	72.22%		
	Anxiogenic	0	35	2	94.59%		
	Anxiolytic	6	0	60	90.91%		
	Class recall	97.36%	46.67%	56.07%		77.26%	0.568
Window size: 2.5s	Control	223	39	46	72.40%		
	Anxiogenic	1	35	0	97.22%		
	Anxiolytic	3	1	61	93.85%		
	Class recall	98.24%	46.67%	57.01%		78.00%	0.580
Window size: 5s	Control	224	39	42	73.44%		
	Anxiogenic	0	36	1	97.30%		
	Anxiolytic	3	0	64	95.52%		
	Class recall	98.68%	78.00%	59.81%		79.22%	0.605
Window size: 7.5s	Control	224	40	48	71.79%		
	Anxiogenic	0	35	1	97.22%		
	Anxiolytic	3	0	58	95.08%		
	Class recall	98.68%	46.67%	54.21%		77.51%	0.569

Table 3: Classification results based solely on descriptive statistics of movement parameters calculated at different temporal windows.

Comparing the kappa values, none of them achieved better results than the 9-zone subdivision in combination with the 5s window size (representing the reliable spatial and temporal scales, as predicted in Sections 5.1 and 5.2, respectively).

6 Discussion

In our case study, the proposed methodology was employed to dissect and quantitatively describe adult zebrafish behavior in the novel tank test [2, 3] under various well-characterized drug class treatments through: 1) assigning unique feature sets to different classes of psychoactive compounds in relation to spatial scale and distribution (e.g., bottom dwelling, freezing, and rapid darting or erratic movements along the bottom in high-stress states versus free, smooth swimming in upper regions of the tank), and 2) building a learning model of fish behavior using previously labeled trajectories to predict the drug treatments of unknown trajectories (achieved through investigation of scaling both in the spatial and temporal domains).

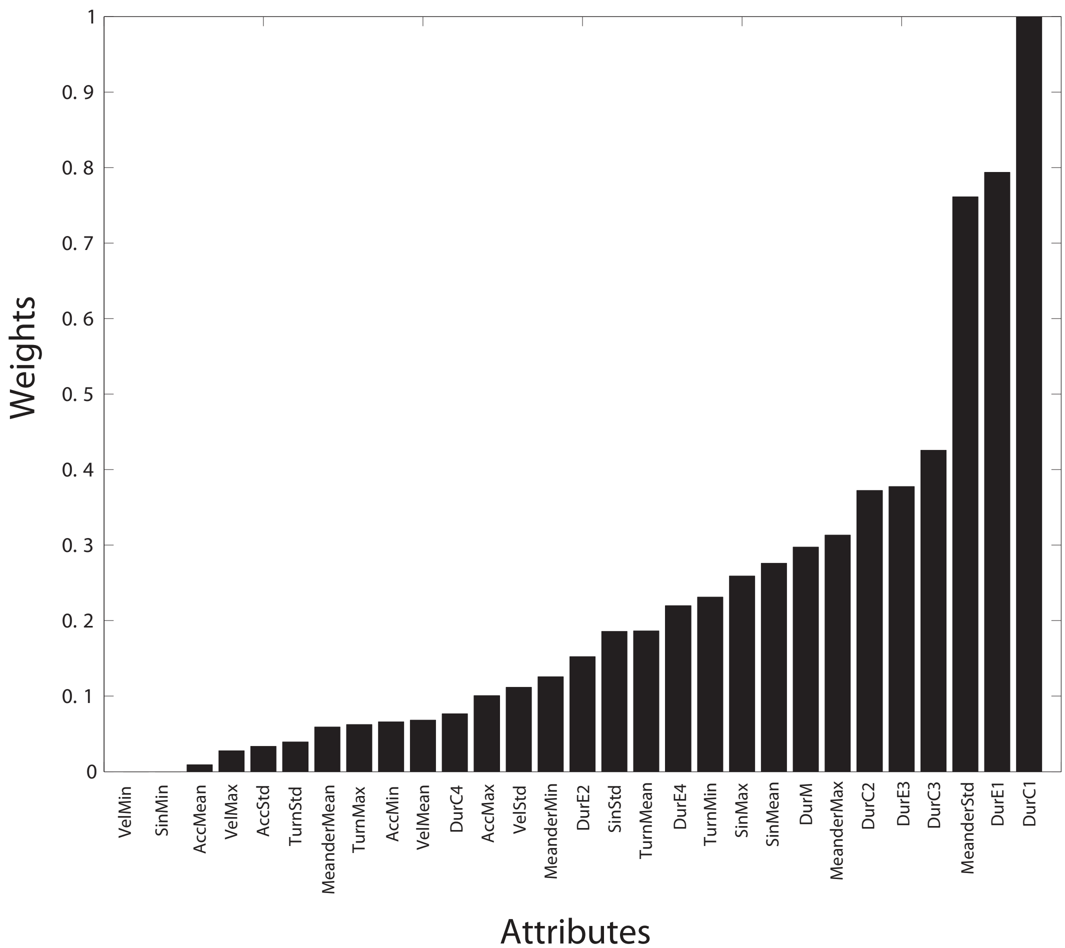

Figure 6: Values of attribute weights from SVM weighting function (see Table 4 for details).

As the results of Section 5.1 show, automated procedures are needed to explore spatial scaling through partitioning underlying movement space. Different classification accuracies delivered at three zoning levels indicates the importance of spatial scaling. In this study, a 9-zone subdivision resulted in better accuracy of classification process, which supports studying zebrafish movement at more finely-grained zones in behavioral pharmacology and drug screening. It also shows that drug treatments affect zebrafish movement behavior in some of the zones, especially corners, which cannot be explored if coarser spatial scales are used. As is well known, spatial aggregation and zoning invariably involves the MAUP. However, the main difference to the common MAUP is that in our case, the selection of the zoning schemes was done based on the biological relevance of the different areas of the testing tank. Exploring this provided the main reason for developing the spatial zoning and scaling in the first place.

The results presented in Section 5.2 indicate the importance of selecting the appropriate temporal interval at which the movement parameters are calculated. Since the raw

Attribute rank	Short name	Full name	Weight
1	DurC1	Duration of time spent in zone C1	1.0
2	DurE1	Duration of time spent in zone E1	0.793
3	MeanderStd	Standard deviation of meandering values	0.761
4	DurC3	Duration of time spent in zone C3	0.425
5	DurE3	Duration of time spent in zone E3	0.377
6	DurC2	Duration of time spent in zone C2	0.372
7	MeanderMax	Maximum of meandering values	0.313
8	DurM	Duration of time spent in zone M	0.297
9	SinMean	Average of sinuosity values	0.275
10	SinMax	Maximum of sinuosity values	0.259
11	TurnMin	Minimum of turning angle values	0.231
12	DurE4	Duration of time spent in zone E4	0.220
13	TurnMean	Average of turning angle values	0.186
14	SinStd	Standard deviation of sinuosity values	0.185
15	DurE2	Duration of time spent in zone E2	0.152
16	MeanderMin	Minimum of meandering values	0.125
17	VelStd	Standard deviation of velocity values	0.111
18	AccMax	Maximum of acceleration values	0.100
19	DurC4	Duration of time spent in zone C4	0.076
20	VelMean	Average of velocity values	0.068

Table 4: Detailed descriptions of the top 20 attribute obtained from SVM weighting.

zebrafish movement data has a very high temporal resolution (sampled at 30fps), the calculation of movement parameters at the original temporal window (or window sizes close to it) may eliminate the actual signal because in a highly granular temporal window, there is not enough time for distinct behavioral events to unfold. Conversely, in a large temporal window (i.e., the full 6 minutes of the test), distinct behavioral states are lost and averaged out within the entire trajectory. Therefore, by using a moving window of around 5s, we are essentially considering a window in which the relevant distinct behavioral states have enough time to play out fully, yet are not be blurred by too large an analysis window.

Overall, our results are in line with the findings of earlier studies in other application domains (e.g., [22] and [21]). However, the novelty of this work is three-fold. First, our methodology extracts movement features in both the spatial and temporal domains and integrates them to obtain a joint model of behavioral classification. Second, after running an analysis across multiple temporal windows, our methodology determines a single reliable temporal scale where the best classification performance is achieved (as we did previously in the spatial domain, Table 3). For both the selection of temporal windows and the spatial partitioning schemes, domain knowledge is used to inform the process. Third, the importance of the combined spatial/temporal features is evaluated through automatic dimensionality reduction techniques based on both local (SVM weighting) and global (GA in conjunction with SVM) search to define the contribution of the individual features and optimize the feature selection process in the classification. As the results from the classification performance analysis show (Tables 3–5), the cross-scale analysis in the spatial and in the temporal domains may be necessary, as it pays off even more when we combine the features from both these domains.

Procedure	Predicted drug class	Observed drug class: Control	Anxiogenic	Anxiolytic	Class precision	Classification accuracy	Kappa coeff.
Subdivision: 3 zones	Control	222	6	42	82.22%		
	Anxiogenic	4	68	10	82.93%		
Temporal window: 5s	Anxiolytic	1	1	55	96.49%		
	Class recall	97.80%	90.67%	51.40%		84.35%	0.721
Subdivision: 9 zones	Control	224	25	17	84.21%		
	Anxiogenic	1	47	0	97.92%		
Temporal window: 0.1s	Anxiolytic	2	3	90	94.74%		
	Class recall	98.68%	62.67%	84.11%		88.26%	0.789
Subdivision: 9 zones	Control	227	25	19	83.76%		
	Anxiogenic	0	49	0	100%		
Temporal window: 1s	Anxiolytic	0	1	88	98.88%		
	Class recall	100%	65.33%	82.24%		89.00%	0.801
Subdivision: 9 zones	Control	224	17	11	88.89%		
	Anxiogenic	2	58	2	93.55%		
Temporal window: 5s	Anxiolytic	1	0	94	98.95%		
	Class recall	98.68%	77.33%	87.85%		91.93%	0.858

Table 5: Classification results based on parameters from both spatial scaling (time spent in different zones) and temporal scaling (descriptive statistics of movement parameters at different temporal windows).

The combination of features from the spatial and temporal domains was then evaluated in a feature selection process in Section 5.3, to assess the importance of different input features in the identification of drug treatments. Biological interpretation can be further attached to the weights of these features. Importantly, the features with the highest weights in Figure 6 and Table 4 are the ones indicating the time spent in different zones, derived from spatial scaling, which indicates the significance of this issue in movement analysis. Time spent in zones C1 (top right corner) and E1 (top edge), respectively, are the ones with the highest weights (and, thus, showing the best discriminating power). The anxiolytic drugs cause the fish to move most of the time in the top of the tank (due to inhibited anxiety), whereas anxiogenic drugs increase anxiety and cause the fish to stay along the bottom, and/or freeze for extended times during high-stress states, hardly traversing the upper zones. On the other hand, the control zebrafish movements are more moderate, as some fish might pass through the upper zones, but not as extensively as those treated with anxiolytic drugs. Thus, these two features (i.e., time spent in zones C1 and E1) may be considered as an indicator of anxiolytic drugs. Conversely, three other highly scoring input features, DurC3, DurE3, and DurC2 (time spent in the two bottom corner zones and the bottom edge zone) can be considered as indicators of anxiogenic drugs. The time spent in the middle zone, DurM, received a relatively high weight, yet was clearly lower than the features related to the top and bottom zones. This may be due to the fact that in both anxiogenic and anxiolytic treatments, visits to the middle zone are rather infrequent, which would yield good discrimination properties. Yet they do occur (particularly in the control treatment), and thus reduce the discriminating power of this feature. While the above input features all stem from spatial scaling, two other highly scoring features, MeanderStd (standard deviation of meandering) and MeanderMax (maximum of meandering) originate from the temporal scaling process. They both relate to the degree of tortuosity relative to the entire path, which again has a biological explanation: anxiogenic drugs generally cause erratic movements with high tortuosity, while anxiolytic drugs induce smoother, extended swim paths. The remaining features score clearly lower weights and thus seem to contribute little to the discrimination of behavioral states. Taken together, this suggests a need for more robust measures apart from the simple statistical descriptors of movement parameters included in this study (i.e., mean, standard deviation, min, and max). In addition, including other distinct classes of drug treatments (i.e., hallucinogenics) may further elucidate the meaning and the value of variance in the observed movement parameters.

7 Conclusions and future work

Our analyses demonstrate the value of exploring both the spatial and temporal domains of movement across different scales in order to yield novel cross-scale behavioral endpoints. To validate the proposed analysis methodology, a dataset of zebrafish movement was employed in order to classify blind trajectories into previously known drug treatments. To our knowledge, such models of spatial scaling through partitioning of the tank arena into different zones have not been applied previously to zebrafish behavioral research. The use of joint cross-scale analysis in the spatial and temporal domains is also novel for neuropharmacological research.

From the point of view of methods development in GIScience, this work has contributed a novel methodology for joint spatio-temporal cross-scale analysis and movement classification. The novelty of this methodology is three-fold: it integrates movement features extracted by cross-scale analysis in both the spatial and temporal domain; it provides a procedure to establish the reliable spatial and temporal scale, that is, the scale at which these features can be reliably measured; and it integrates the use of machine learning methods to optimize feature selection for classification. Our work resulted in the following key findings:

- Cross-scale analysis outperforms simple fixed scale analysis. This holds for both the spatial and the temporal domain individually, but the improvement of classification performance is even more substantial if features from the two domains are combined. Thus, joint spatio-temporal cross-scale analysis has a clear potential, and should be investigated further for other applications of behavioral classification.
- Different scopes of the underlying movement space (or, as some authors call it, context) should be explored at different extents in order to investigate the process of spatial scaling and identify the reliable spatial scale.
- Exploring the temporal scaling behavior of movement parameters in relation to different temporal window sizes allows the investigators to automatically select the reliable temporal scale. However, more robust methods than boxplots used in this study may be investigated further.
- ML methods can be helpful in distinguishing known behavioral mechanisms based on a combination of features extracted from both the spatial and temporal domains,

given the high number of multiply interrelated input features resulting from a joint spatiotemporal classification strategy.

As part of our future work, two research strands seem particularly relevant. First, the proposed methodology can be adapted to other application domains, where different movement patterns from those of the present case study prevail. This strand is expected to generate insights regarding the generalizability of the methodology. As a second strand, we plan to develop new measures based on the arena partitioning applied in this work. These measures can be capable of capturing inherent spatial and temporal properties of movement within different zones. Thus, a spatial measure may be used to determine whether fish display preferential, stereotypic movement patterns between zones, or their swimming behavior was more variable throughout the arena. Likewise, a temporal index can be used to determine whether fish show substantial preference for a particular zone over others, or their activity is more evenly distributed during the experimental trials. Additionally, the variation of movement parameters within zones could also be investigated beyond simple statistical descriptors. For this, additional drug treatments (hallucinogenics) will be included to clarify the variance and importance of those movement parameters that received lower weights in our current experiments. If successful, these analyses may have several important practical applications, enhancing drug screening for biomedical research.

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Chapter

3

Capability of movement features extracted from GPS trajectories for the classification of fine-grained behaviors

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Capability of movement features extracted from GPS trajectories for the classification of fine-grained behaviors

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Abstract

Recent advances in tracking technologies provide an unprecedented opportunity for a better understanding of animal movement. Data from multiple sensors can be used to capture crucial factors deriving the behaviors of the animal. Typically, accelerometer data is used to describe and classify fine-grained behaviors, while GPS data are rather used to identify more large-scale mobility patterns. In this study, however, the main research question was to what extent fine-grained foraging behaviors of wading birds can be classified from GPS tracking data alone. The species used in this study was the Eurasian Oystercatcher, *Haematopus ostralegus*. First, a supervised classification approach is employed based on parameters extracted from accelerometer data to identify and label different behavioral categories. Then, we seek to establish how movement parameters, computed from GPS trajectories, can identify the previously labeled behaviors. A decision tree was developed to see which movement features specifically contribute to predicting foraging. The methods used in this study suggest that it is possible to extract, with high accuracy, fine-grained behaviors based on high-resolution GPS data, providing an opportunity to build a prediction model in cases where no additional sensor or observational data on behavior is available. The key to success, however, is a careful selection of the movement features used in the classification process, including cross-scale analysis.

Keywords: Movement analysis, GPS, accelerometer, foraging behavior, movement parameters, classification

1 Introduction

Classification of movement trajectories into different behavioral categories has become a recent trend in many domains, including e.g. movement ecology, transportation, and urban management. In ecology especially, behavioral classification is an important analysis step, because knowledge about behaviour provides important input to many inferences about physiology, energy balance, and evolution of particular species. While various types of data are being used for animal behavior classification, the use of features based on movement trajectories (e.g. GPS) is still quite uncommon (see [18]). The main reason for this has been that when the goal is to distinguish between behaviors (especially fine-grained behaviors, e.g. foraging vs. non-foraging), the temporal sampling rate is typically low or irregular in relation to the variability inherent to the movements that are considered. However, due to recent advances in tracking technologies, it has become feasible to collect high-resolution GPS and sensor data on a more regular basis. For example, GPS has been integrated into operational systems with other sensor technologies to collect temperature, activity, proximity and mortality data from terrestrial species and birds [1, 19, 21].

This study aims at developing a classifier to identify foraging behavior in a shorebird, the Eurasian Oystercatcher (*Haematopus ostralegus*), based on GPS trajectory data. This species has been intensively studied ([6]) to answer questions on e.g. foraging ecology, resource use and territoriality in shorebirds. The GPS trajectory data for individuals may be more accurate and less biased than the sighting or experimental data that are available from previous research and may thereby lead to more robust answers. Especially the time spent on foraging as well as foraging locations form important variables to measure foraging strategies and efficiency.

Accelerometer data can be used to identify various behaviors of an oystercatcher, including foraging [18], the same way as depth loggers are used to record ‘dives’, salinity sensors to record ‘being in the water’, or light sensors to record ‘being in a burrow’ [7, 9, 10, 13, 17]. However, accelerometers are not yet in widespread use today and a lot of trajectories with location-only information have been collected and will continue to be collected. According to Movebank (www.movebank.org) as one of the major repositories of animal movement, more than 90% of the data collected there is location-only. Therefore we attempt to develop features and a classifier that is based exclusively on location data. In order to do so, the model of [18] is first used to generate the behavioral labels and then serves as a baseline to train and evaluate the classification model that is based exclusively on movement features extracted from GPS trajectories. Thus, the main research question is to what extent fine-grained foraging behaviors, on the example of oystercatchers, can be classified from GPS tracking data alone.

2 State of the art

A variety of methods for inferring behaviors based on sensor data have been proposed. Among movement parameters computed from trajectories, velocity has been used to distinguish between traveling and resting during bird migration [9], identification of different behavioral categories in combination with accelerometer readings [18], and distinguishing behavioral drug treatments in neuro-pharmacology [3]. A combination of velocity and direction has also been used in [20] for defining behaviorally consistent movement units. Sinuosity, on the other hand, has been used for detection of behavioral change in animal movement [16], foraging movement and activity patterns of seabirds [25], and for distinguishing between trajectories of different vehicles types [4]. Wavelet analysis has also been applied based on the values of net displacement [23] and velocity [15] for studying behavioral patterns in animal movement.

Accelerometer data, on the other hand, is increasingly being applied to characterize behavior or describe certain movements, e.g. of humans (using accelerometers on smart phones) [24], domestic animals [12], as well as free-ranging animals like birds [10, 14, 17, 18] and marine mammals [7, 13].

3 Methods

In this paper, we use a data set of combined GPS and accelerometer observations, obtained in the Dutch Wadden Sea, south of the island Schiermonnikoog on 12 individual Eurasian Oystercatchers (*Haematopus ostralegus*). The birds were tagged with UvA-BiTS devices [1], and samples from June and July 2009 as well as from May and June 2011 were used in this study. There were different sampling intervals in the samples, but for the major part of the data it was one location per 13 seconds (the second large group was with intervals of 6 seconds and the intervals were always lower than one location per 45 seconds).

We first classified the Oystercatcher trajectories as ‘foraging’ versus ‘non-foraging’ based on accelerometer data, using a classification model introduced in [18]. In [18], the model had been calibrated for the same species at approximately the same location while using the same devices. Based on the labeled data set we then started to develop features and classifiers based on GPS data only. The following (movement) features were calculated for each fix of the trajectories: distance traveled; velocity; turning angle and its dependent variables including angular velocity (turning angle over time) and meandering (turning angle over distance traveled). See [3] and [4] for some example uses of these parameters. Furthermore, two parameters indicative of path curvature were generated: sinuosity and the Multi-Scale Straightness Index (MSSI; see [16]).

A decision tree was selected for the classification process, using the implementation in RapidMiner 5, (RapidMiner, http://rapidminer.com/). A top-down procedure is applied based on the CART learner to traverse the tree [2]. Whenever a new node is created at a certain stage, an attribute is picked to maximize the discriminative power of that node with respect to the examples assigned to the particular subtree. This discriminative power is measured by the information gain ratio [2]. The information gain ratio can be considered as the importance of the selected attributes in the design of the tree. This was the reason for choosing decision trees in this study: they can give an insight into the relative importance of different movement features in the identification of behaviors, by their appearance as a node splitter. Other machine learning methods such as SVM might even result in a slightly better classification performance (as preliminary test have shown), but since improving the classification performance was not the main objective of this study, those classification methods were not chosen. A 10-fold cross-validation procedure was applied to see how good the resulting classification performances are when different movement parameters were used as input variables. For the evaluation of the performance of classification models, we looked at different criteria, such as overall classification accuracy and Kappa values, as well as precision and recall values in the case of individual classes, specifically when we examined the foraging class.

Since the sampling intervals differed between data sets and earlier studies had demonstrated the importance of scale in the computation of movement parameters, we performed a cross-scale analysis, employing the method proposed by [11]. Values of movement parameters for each fix of the trajectory were computed across a series of sliding windows with different sizes of w, in a segment where $w/2$ fixes exist before and after the central sample point of interest.

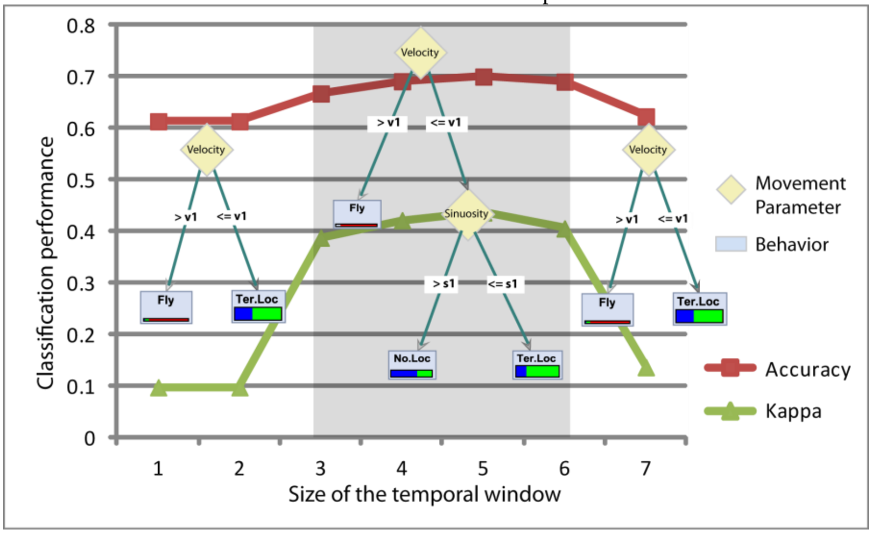
4 Results

4.1 Attribute selection

The classification performance was first acquired individually for all parameters. At first glance, velocity and distance traveled did seem to have a large impact on the classification results, which is in accordance with the findings of the studies having used these parameters [9, 15, 20, 23]. Turning angle, angular velocity and meandering, on the other hand, were not so helpful, which might be due to the positional error in GPS observations, especially at lower speeds. For the path curvature parameters, including MSSI and sinuosity, the values were computed across different scales. MSSI is inherently a multi-scale measure and similarly to sinuosity, it gives a ratio of the beeline distance between two points of interest and the actual distance traveled. However, the difference between the measures is that distance is computed multiple times, over a variety of scales for both temporal granularity and observational window [16]. We chose a granularity value of 2 and window sizes of 4, 8, 12, 16, 20 and 24, respectively. When individual sets of MSSI values were used, they were not helpful in distinguishing between classes, but as will be shown later, when geographic location is integrated (latitude and longitude), they do show a great potential in improving the results.

The same cross-scale approach was employed for sinuosity. The window sizes chosen for calculation of sinuosity start from the surrounding fixes (window size of 1), increasing up to 7 points before and after (1, 2, 3, 4, 5, 6, 7). Then, each set of sinuosity values computed at different scales were considered separately as input features in the classification, to see how the performance and the resulting decision tree would vary. We used the 3-class category (no locomotion, terrestrial locomotion and fly) of [18] in this part, as we wanted to investigate the importance of scale effects on a known model. In the subsequent process, however, the classification is only between foraging and non-foraging classes, by considering the outputs of the cross-scale analysis.

Figure 1: Variation of classification performance (Accuracy and Kappa) according to different temporal window sizes used for calculation of movement parameters.



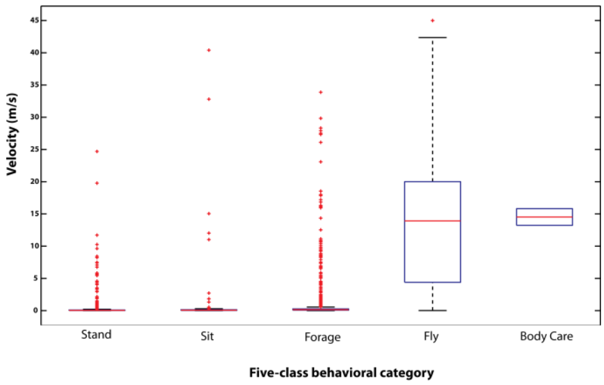
Interestingly, only after using a window size of 3 the role of sinuosity is starting to emerge in the structure of the decision tree (Figure 1). At the same time, for the window sizes of 3 to 6, higher classification accuracy and Kappa values were achieved. The tree structure for these window sizes was always the same, with velocity at the top, followed by sinuosity on the second level of the tree hierarchy (Figure 1). Since the window size of 5 scored relatively higher classification performance, it was selected as the window size at which sinuosity values can be reliably computed and considered as input features for the final classification.

4.2 Foraging versus non-foraging

In [18], a 5-class model has been calibrated that we are applying in this study; however we aggregate the output from 5 to 2 classes. First, since the fly class in the 5-class model can be easily distinguished from the stand, sit and foraging classes by using only the velocity parameter (Figure 2), the fly class is eliminated from the further analysis. The velocity values for the body care class are surprisingly high, which might be due to an error in the behavioral classification resulting from the accelerometer data. Nevertheless, since there were only two points labeled as body care, removing the fly class is still reasonable. Afterwards, all the non-foraging classes were aggregated and compared to the foraging class, resulting in a binary classification between a foraging class and a non-foraging class. Eliminating the fly class will help since there is a huge difference in the movement parameter values of the fly class and the rest of the classes, respectively, and if they were aggregated into a single class of non-foraging behaviors, it would have been difficult for the classifier to discriminate them. So, by first removing the fly class, only the sit, stand and body care classes will be aggregated into the non-foraging class. These behaviors share more similar movement characteristics.

In the end, there were 6486 fixes labeled as foraging and 4725 as non-foraging. Prior to applying the final classification, values of the selected attributes including distance traveled, velocity, sinuosity and MSSI are discretized into 3 bins, as it will help in improvement of the classification performance of the decision trees [5].

Figure 2: Boxplots of variation of velocity for five behavioral classes (Stand, Sit, Forage, Fly and Body Care).

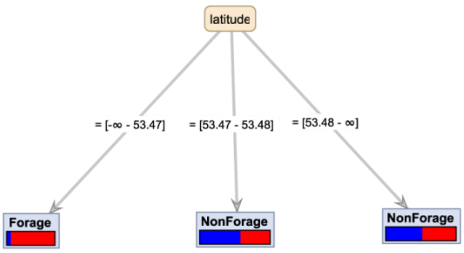


4.3 Importance of geographic context

To see whether knowledge about geographic context, represented by the geographic location of the birds, will help in identifying the behaviors, values of latitude and longitude of each fix were considered as input features in a classification tree. The resulting decision tree using only geographic location is shown in Figure 3. Apparently, latitude is a dominant variable in identifying behaviors, resulting in a rather high classification accuracy of 67.16 %. However, very high classification precision (91.27 %) and at the same time very low recall values (50.40 %) does not indicate a robust performance. Nevertheless, this model will be considered as a baseline in order to compare with the following classification experiments, where values of movement parameters are integrated as well.

Subsequently, two separate decision trees based on the values of MSSI and sinuosity were developed (Figure 4). For each of these models, geographic location values were also integrated in order to make it possible to compare these to the baseline model developed in Figure 3. Additionally, since the importance of velocity and the distance traveled have been already emphasized, their values were also considered as input features in the classification model. Interestingly, both of the trees start with latitude at the top and then movement parameters are emerging at the lower levels (Figure 4).

Figure 3: The baseline decision tree for distinguishing foraging versus non-foraging developed based on location information, i.e. latitude and longitude. The confusion matrix is based on 10-fold cross-validation results.



Predicted / True	Non-Forage	Forage	Class Precision
Non-Forage	3949	3217	55.11%
Forage	313	3269	91.26%
Class Recall	92.66%	50.40%	
Overall performance			
Accuracy: 67.16%	Precision:91.27%	Recall: 50.40%	

5 Discussion

In the baseline classification model (Figure 3), the choice of latitude as a predictor variable in the decision tree can be understood from the east-west orientation of the Wadden island Schiermonnikoog, which provides the habitat of the studied individuals, located along the southern shore. The areas south of latitude 53.47º consist of mudflats with a short emersion time and high shellfish density. The area between 53.47º and 53.48º contains a combination of mudflats with long emersion time (which relates to a low shellfish density) and salt marshes. The area north of 53.48º contains salt marshes and meadow land. On the mudflats the Oystercatchers will feed on shellfish (mainly Baltic tellin – *Macoma baltica*) and ragworm (*Nereis diversicolor*). Conversely, on the saltmarsh and meadows they eat earthworms and insect larvae. The differences in habitat structure and prey types are reflected in different movement patterns.

As shown in Figure 4, the decision trees based on sinuosity and MSSI are not only improving the classification performance, but also give a more comprehensible overview of the importance of the movement features involved in combination with the underlying geographic location.

In the case of sinuosity, the leaves of the decision tree seem to be reasonable. Low values, indicating a smoother path, are labeled as foraging, whereas large values, indicative of a more complex path, are related to the non-foraging class (the path is more curved while the bird is sitting, standing or body caring due to GPS uncertainty). The values in the medium category are broken down again and distance values appear at the next level of the tree. The leaves at these levels are also sensible, as low and medium values of distance traveled are labeled as non-foraging and higher values as foraging. At the same time and as shown in Figure 1, it is worth noting that the usefulness of sinuosity is only revealed when the values are computed across different scales. In other words, if we had only used the sinuosity values computed at the original temporal rate, we could not have obtained the same results.

The resulting tree structure for MSSI is rather difficult to explain, but what looks interesting is the hierarchy in the structure of the tree (starting with window size 24x at the top and then 8x and 4x). Also, the tree is mostly dominated by foraging at the top (24x and 8x), while non-foraging only appears to be more dominant at the smallest scale (4x).

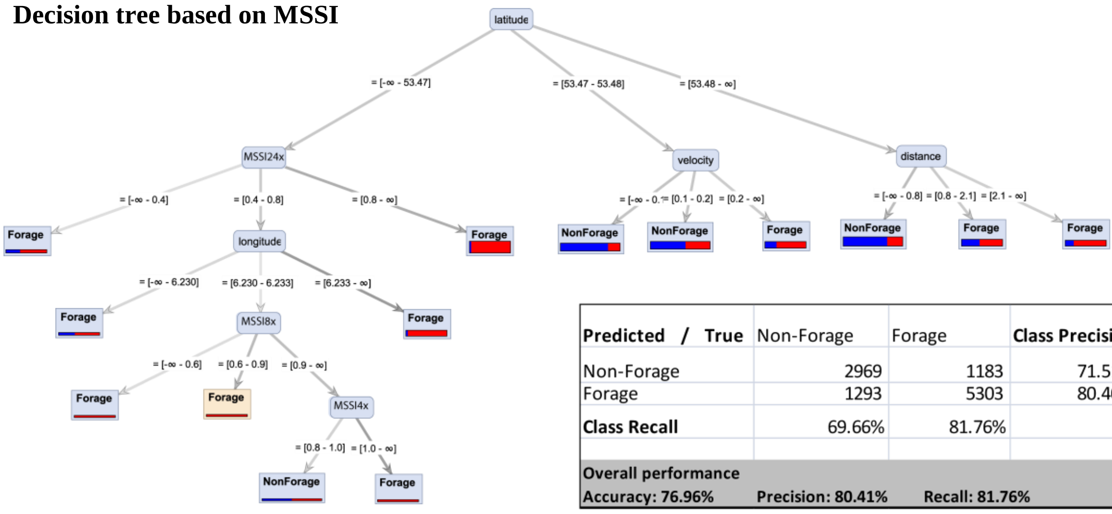
Resulting classification performances for the MSSI and sinuosity trees are comparable, with slightly better results for the sinuosity tree. As shown in the tables of Figure 4, overall accuracy and recall values are better for the sinuosity tree, whereas the MSSI tree results in a better precision value. Comparing to the baseline model developed based on geographic coordinates only (Figure 3), the classification performance is considerably better for the MSSI and sinuosity classification trees, leading to classifiers with an overall cross-validation accuracy of 0.78. This indicates a clear potential of parameters extracted from trajectories for the identification of movement-related animal behaviors.

6 Conclusions

To our knowledge, most of the works based on movement features (e.g. sinuosity and MSSI) do not use a classification model and are rather descriptive. Sinuosity, for example, has only been applied to flying birds ([8, 22]) and not yet to wading birds that are foraging on the ground. Thus, a classification model based on trajectory features, as presented in this study, seems a useful contribution to exploit information from animal-borne sensors to further understand and model animal behavior. However, apart from sinuosity and MSSI, there are other features that have not been used yet, including e.g. first passage time, scale invariance and fractal dimension. Exploration of these features can be considered as part of future work. Furthermore, since using GPS trajectory data often stumbles on problems with accuracy, an assessment of the positional accuracy and its consequences for the distinction of behavioral types seems important in order to fully appraise the potential of the proposed approach.

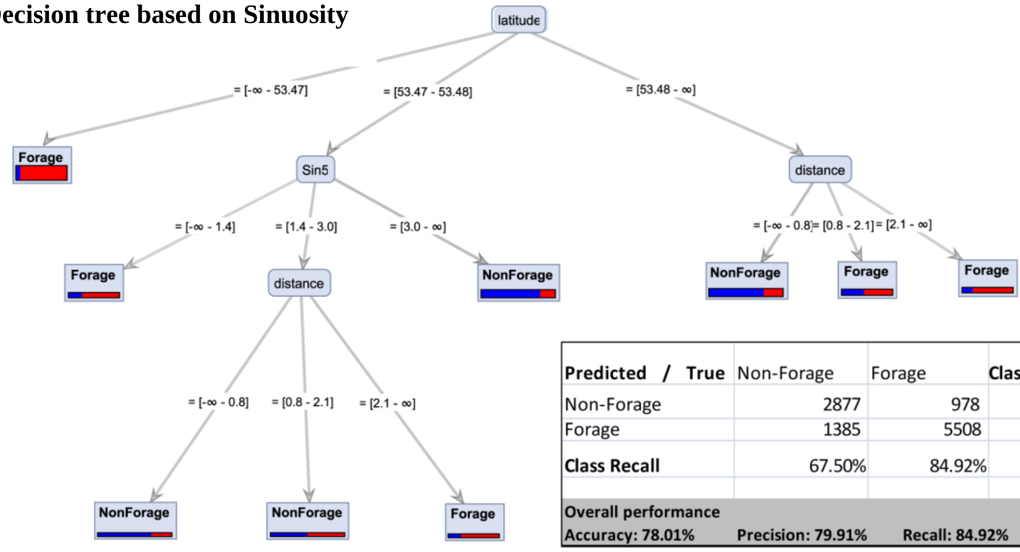
Figure 4: Two developed decision trees based on the two employed movement features (together with velocity and distance traveled): Sinuosity calculated at window size of 5 (shown as sin5) and MSSI calculated at window sizes of 4, 8, 12, 16, 20 and 24. Depending on their importance, each of these features are emerging at different levels of the corresponding decision trees. Note that the confusion matrices related to each tree are based on 10-fold cross-validation results.

Decision tree based on MSSI



Predicted / True	Non-Forage	Forage	Class Precision
Non-Forage	2969	1183	71.51%
Forage	1293	5303	80.40%
Class Recall	69.66%	81.76%	
Overall performance			
Accuracy: 76.96%	**Precision: 80.41%**	**Recall: 81.76%**	

Decision tree based on Sinuosity



Predicted / True	Non-Forage	Forage	Class Precision
Non-Forage	2877	978	74.63%
Forage	1385	5508	79.91%
Class Recall	67.50%	84.92%	
Overall performance			
Accuracy: 78.01%	**Precision: 79.91%**	**Recall: 84.92%**	

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Chapter

4

Developing and integrating advanced movement features improves automated classification of Ciliate species

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RESEARCH ARTICLE

Developing and Integrating Advanced Movement Features Improves Automated Classification of Ciliate Species

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Abstract

Recent advances in tracking technologies such as GPS or video tracking systems describe the movement paths of individuals in unprecedented details and are increasingly used in different fields, including ecology. However, extracting information from raw movement data requires advanced analysis techniques, for instance to infer behaviors expressed during a certain period of the recorded trajectory, or gender or species identity in case data is obtained from remote tracking. In this paper, we address how different movement features affect the ability to automatically classify the species identity, using a dataset of unicellular microbes (i.e., ciliates). Previously, morphological attributes and simple movement metrics, such as speed, were used for classifying ciliate species. Here, we demonstrate that adding advanced movement features, in particular such based on discrete wavelet transform, to morphological features can improve classification. These results may have practical applications in automated monitoring of waste water facilities as well as environmental monitoring of aquatic systems.

Introduction

Over the past decades, various tracking technologies such as the Global Positioning System (GPS) and sophisticated video techniques have become accessible to scientists and enabled the recording of large amounts of data about the movement paths of individual organisms [1–4]. GPS tags or collars have the advantage that auxiliary information on the individual can be collected when the device is attached, which can subsequently help in understanding the differences between collected movement paths. Typically the target of these movement analyses is to infer movement patterns corresponding to behaviors such as foraging or dispersal [5,6] or to link the genotype and behavioral phenotype of organisms [7]. However for inferring other sorts of information such as gender or species, remote techniques such as video tracking are neither capturing nor marking the individual and hence auxiliary information on the species or gender of the tracked individual is not known. Previous studies found that it is possible to distinguish trajectories based on individual features such as their genotype and gender [7], the degree of light availability [8] or whether individuals were in resource poor or rich environments [9]. Moreover, individual movement may also be indicative of the internal state of the moving individual, which can be used to evaluate the effect of toxic substances in the environment or laboratory based toxicity assays [10]. Developing techniques to infer behavior from movement paths is an active field of research [11–14] especially for GPS-based movement data, but here we focus on classifying trajectories regarding species identity. This problem is less well studied as remote tracking studies, where multiple species (or genotypes) interact, are still relatively rare in ecology, but are expected to increase rapidly with high-throughput analysis based on image and video analysis [3]. Regardless of the tracking technique used, all these applications have in common that characteristic features of the movement have to be associated to known classes, such as behavior or species identity, which is generally referred to as *movement classification*.

Movement classification represents a particular set of problems, where either entire movement paths (trajectories) or parts of trajectories (i.e. subtrajectories) are assigned to classes with respect to some *a priori* unknown criterion. As in all classification problems, training in which the class is known is used to infer criteria (characteristic features of the data) that are able to reliably predict the class of unknown cases. Here, we address how different features of the movement data contribute to classification accuracy.

In particular, we examine how movement data can contribute to classifying different species of ciliates (*Kingdom Protozoa*, *Alveolata*, *Ciliophora*). Ciliates are widely found in all types of fresh-water and marine environments and fulfill important functions in natural ecosystems such as controlling the abundance of bacteria by predation and are themselves important food for small invertebrates such as crustaceans (e.g. Daphnia water fleas) [15,16]. Ciliates are also widely used as model organisms in studies in ecology and evolutionary biology where experimental microcosms (i.e. small-sized standardized containers with tight environmental control) are used [17]. Only recently due to the advent of automated video analysis, quantitative traits such as movement (e.g. speed, linearity) and morphology (e.g. cell size, cell shape) can be measured on large numbers of individuals automatically and hence are explicitly considered in such microcosm studies [17].

Morphological attributes are commonly used to classify ciliate species [18–21]. Our goal here is to investigate how movement of ciliates can contribute to their classification, as well as the performance of movement features only in the classification. We make this distinction to draw general conclusions accounting for cases where information on morphology is missing and only movement features as classification inputs are available. Microbial species are often characterized by little morphological differentiation, even though they are known to be physiologically and genetically diverse [22]. Hence, movement behavior may be a better indicator of taxonomy than morphology, or at least assist with morphological based classification. Automated video based classification of ciliate species has potential application in different fields, for instance for the automated monitoring of waste water facilities as well as environmental monitoring of aquatic systems more broadly [21].

Whereas previous analysis of the data has shown that movement can improve classification [23], here we aim to systematically explore the contributions of more sophisticated movement analysis techniques to classification. Feature extraction from movement data is complicated by two characteristics of movement. First, considering that movement operates through space and time, representing and integrating both of these domains remains a challenge [24]. Respectively in movement classification, relevant features in the spatial and temporal domains should be extracted in order to capture spatiotemporal (as opposed to separate spatial, or temporal) characteristics of the moving individual under study. Second, the patterns underlying the movement classes might relate to multiple spatial and temporal scales (i.e. instantaneous, diurnal or seasonal) and using only the original temporal granularity for calculating MPs is a strong oversimplification of actual movement patterns [25]. Thus, distinguishing features may only become apparent if multiple analysis scales are considered [26].

In this study, wavelet analysis is investigated as a cross-scale analysis approach for extracting features in movement classification. While the related technique of Fourier transform is helpful for identifying periodicities in stationary time series, it will fail on time series where periodicity occurs only irregularly through the data set [27,28]. This is the case for most movement time series, as these are often non-homogeneous, made up of a combination of discrete behaviors. For example, animals may spend more time in a nesting or resting place and thus show only limited movement [29]. In contrast, other places may be used intermittently for foraging and animals may show more movements and hence higher activity [30]. Hence, we test whether integrating features based on wavelet analysis could improve classification due to its ability to detect non-stationary patterns in movement data, where transient types of activity occur. Moreover, features based on the wavelet transform can also be useful for relating these activities to other factors (e.g. physiological, ecological, contextual, etc.) affecting movement [31,32]. Thus, features based on wavelet transform are considered as a complementary tool for identifying the elements of periodic patterns in the movement data.

The contributions of this paper are two-fold. First, we develop a model for movement classification purely based on quantitative features, where each feature measures particular aspects of movement. Three sets of movement features are used (movement parameters only, approximate entropy (ApEn), and wavelet coefficients) and compared to the baseline model that uses only morphological features. We show how gradually adding features improves the performance of the classification model. Secondly, we demonstrate that careful selection and integration of movement features will lead us to comparable results, irrespective of the classification method employed, i.e. decision trees (DT) vs. support vector machines (SVM). Although the results of the classification method might differ among the individual sets of features used, once all features are integrated, the obtained results are comparable between the two classification methods.

Methods and Materials

Overview of movement classification

As in any general classification problem, several steps need to be taken in movement classification in order to make the transition from the observational movement data to the final classes, which we have schematized in Fig 1. The movement parameters (MP, e.g. speed, acceleration, turning angle, etc. [33]) are calculated from the raw movement data. Since trajectories are ordered by time, we get a time series of MP values, which we call an MP profile. The obtained MP profiles are converted to a set of feature vectors, on which statistical descriptors (i.e. mean, standard deviation, median, etc.) may be computed. In this study, we use approximate entropy and discrete wavelet transform to provide additional features. The classification model is built by using the relevant extracted features as quantitative inputs for the model and relating these to the known classes.

Extraction of movement features. Seven movement parameters (i.e. distance travelled, speed, acceleration, turning angle, angular velocity, meandering and sinuosity) were calculated. These values were aggregated into concise representations (i.e. features) to be used in the classification. Features can be related to individual fixes [25], to a short series of fixes, for instance by segmenting the trajectories [34], or to all fixes in a recorded trajectory [26]. Here, we consider

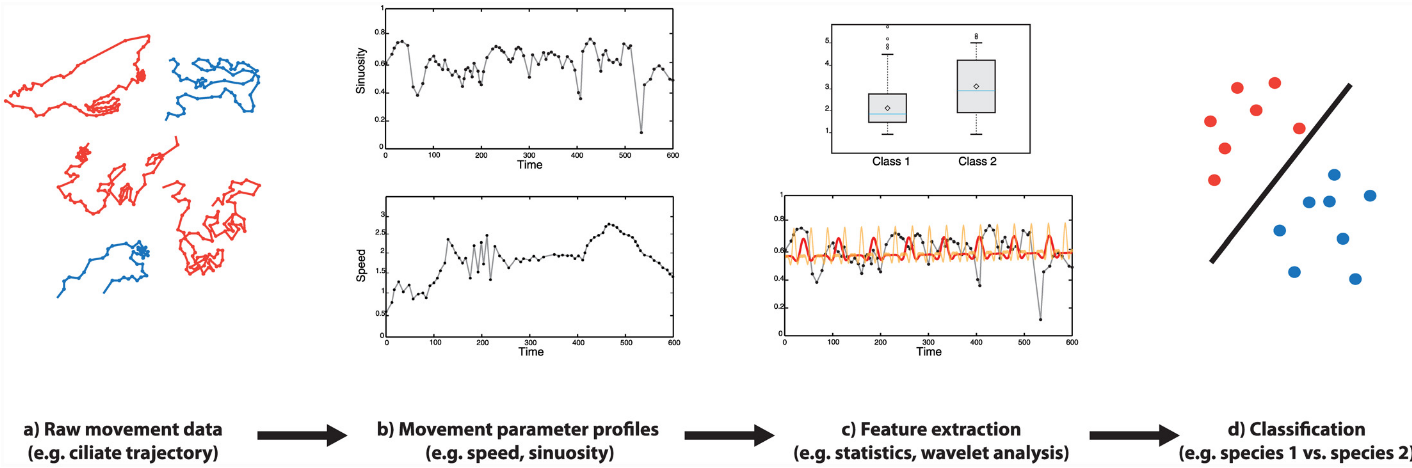

Fig 1. Overview of the movement classification process. a) raw trajectories of two species of ciliates consisting of time-stamped X- and Y coordinates; b) movement parameters are calculated from the locations and MP profiles through time are obtained; c) extraction of features, for instance, summary statistics of movement parameters (upper panel) or wavelet coefficients (lower panel); d) classification of species based the movement features extracted.

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two categories of features: aggregate features computed on the whole trajectories and features based on the wavelet transform.

Aggregate movement features. Moment statistics of movement parameters are the most common form of aggregate features used in classification models. By describing general variations present in the movement data, these features may already differentiate between movement classes at a certain scale. Different moment statistics may be used, such as minimum, maximum, median, mean, standard deviation, etc. However, in the transition from the raw movement trajectories to the summarized representation of classification features, an information loss will be introduced: by the use of only aggregated features at a certain scale, clearly not all aspects of movement can be detected [26].

Therefore, we also used ApEn values as an added feature in the classification model [35,36]. ApEn is a method from time series analysis for quantifying regularities and fluctuations in sequential data [35]. Since moment statistics might ignore subtle changes in the structure of MP profiles, ApEn values are calculated to investigate the regularity or to detect dominant fluctuations in such profiles. As a measure of system complexity, higher values of ApEn suggest a more random distribution (i.e. less predictable profile with complex structure), while a smaller value implies less complexity and more regularity (i.e. highly structural profiles containing many repetitive patterns). In order to better distinguish between movement classes, approximate entropy of MP profiles can be used to show how the structural complexity of particular movement parameters varies over time [36].

Feature extraction based on wavelet analysis. Based on the MP profiles, the discrete wavelet transform (DWT) was used in order to decompose the movement signal into different levels (see S1 Text, S1 and S2 Figs for a detailed description of the wavelet transform performed). Wavelet analysis can reveal features such as temporal autocorrelation or periodicity patterns in the movement data [37,38], which may go undetected through the aggregate features mentioned before. In each decomposition level, an approximation and a detail sub-band is obtained, yielding two sets of wavelet coefficients. These two sets of information are sufficient to reconstruct the signal [39,40]. Three moment statistics of wavelet coefficients in each sub-band were considered as input features. These include the mean of the absolute values of the coefficients in each sub-band; average power of the wavelet coefficients in each sub-band; and standard deviation of the coefficients in each sub-band. There are two parameters to be set in a DWT analysis: the first is the choice of mother wavelet function, through which the signal is passed in order to characterize the variations. All the wavelets used at different levels of decompositions are scaled and shifted versions of the same mother wavelet function. A Daubechies wavelet (db4) was chosen as the mother wavelet function, due to its superior performance, and order 4 selected to detect the discontinuities in the signals [30,41]. The second parameter is the number of the decomposition levels to provide approximation and detail sub-band at different scales. Considering that possible decomposition levels depend on the length of the trajectories, this was chosen to be 5 in this study.

Other studies have used the distance travelled and speed in the wavelet analysis [30,31,38]. For both, periodic patterns in the profile may be expected whereas for other parameters, it would be rather difficult to interpret the periodicity occurring in the profiles. In the experiments reported here, we used the profiles of the distance travelled to extract the wavelet-based features.

Experiment

Model species

We used 8 species of small, single-celled ciliates as model species for this study: *Paramecium caudatum*, *Paramecium aurelia*, *Blepharisma japonicum*, *Colpidium striatum*, *Colpidium campylum*, *Cyclidium glaucoma*, *Tetrahymena thermophila* and *Loxocephalus* sp.

Each ciliate stock was cultured separately in a jar of 240 ml volume covered by aluminum cover to allow air exchange but prevent contaminations. Jars contained protist pellet medium (Carolina Biological Supplies), at a concentration of 0.55 g per liter of Chalkley's medium and two wheat seeds for slow nutrient release. In addition, the medium contained three bacterial species (*Serratia fonticola*, *Brevibacillus brevis* and *Bacillus subtilis*) as food source for the ciliates. Jars were kept in a temperature-controlled incubator at 15° Celsius. Stocks were transferred monthly by pipetting a small subsample of the previous culture into a jar prepared as described above. Because the different ciliates used show quite pronounced intrinsic differences in cell density under the same culture conditions [17], variable numbers of trajectories were obtained per species.

Data collection

Sampling was done on two dates (24.03.2014 and 07.04.2014) with cultures being 20 days old and thus in the stationary phase. We collected movement trajectories by videoing subsamples of the cultures. To do so, we transferred 1 ml of ciliate culture into a Sedgewick Rafter counting chamber, which was placed under the objective of a stereomicroscope (Leica M205 C) at 25x magnification. We took 20 second video sequences at a frame rate of 25 frames per second using a mounted digital CMOS camera (Hamamatsu C11440) resulting in a total of 500 frames. Dark field illumination was used such that ciliates, transparent in bright field microscopy, appear white on black background; this greatly facilitates the segmentation of videos. We used the software BEMOVI to extract morphological features and movement trajectories of individual cells [23]. Six morphological attributes were extracted for each fix: grey value (pixel intensity from 0 [black] to 255 [white]), area (i.e., cross section), the perimeter, major and minor axes of a fitted ellipse and the aspect ratio (i.e. minor axis/major axis [AR]). Trajectories were filtered by a standardized procedure to get rid of spurious trajectories due to swimming debris: trajectories for analysis were required to show a minimum net displacement of at least 50 pixel, 10 fixes per trajectory and a detection rate of 80% (i.e. a trajectory with a duration of 10 frames has to have at least 8 fixes) and a median step length of greater than 2 pixels. This resulted in 3957 trajectories in total.

Analysis

Different movement features sets were first tested to assess their predictive power for finding species classes. These include all combinations of aggregate movement parameter (MP), approximate entropy (ApEn) and wavelet (Wav) features, leading to 7 movement models including: MP, ApEn, Wav, MP+ApEn, MP+Wav, ApEn+Wav, MP+ApEn+Wav. According to their performance, selected movement feature sets are later integrated to morphological features. The feature sets selected for this study (after initial performance evaluation) and the numbers of features are listed below:

1. *Morphology*: Mean and standard deviation for the 6 morphological attributes along the trajectory (12 features per trajectory)
2. *MP only*: Mean, standard deviation and median values for 7 movement parameters, i.e. distance travelled, speed, acceleration, turning angle, angular velocity, meandering and sinuosity (21 features per trajectory)
3. *MP+ApEn*: Adding ApEn values for all the movement parameter profiles to the MP model (7 additional features per trajectory; total of 28 [= 21+7]).
4. *MP+ApEn+Wav*: Adding wavelet features using profiles of the distance travelled (30 additional features; total of 58 [= 28+30])
5. *MP+Morph*: Integrates 21 *MP only* features and 12 morphology features (total of 33 [= 21 +12])
6. *MP+ApEn+Wav+Morph*: Integrates all features, i.e. morphology and all features based on movement (total of 70 [= 58+12])

Since the number of the features notably increases, a feature selection process was employed to determine the ultimately relevant features in the classification. An evolutionary feature selection process by Genetic Algorithms (GA) in conjunction with the classifier (i.e. DT and SVM) was used to evaluate the significance of the added features in the classification. For SVM, we applied a radial basis function (RBF) with two kernel parameters of $C = 20$, which is a penalty parameter imposing a tradeoff between training error and generalization performance of SVM classifier and $\gamma = 0.001$, which is an exponent factor in the RBF function. In case of DT, a top-down procedure is applied based on the CART learner to traverse the tree, using the following parameter setting: maximal depth of tree = 20, minimal size for split = 4 and confidence value of 0.25. The reported results are based on a 10-fold cross-validation for both classifiers in the feature selection process, with the following parameter settings for GA: population size: 10, number of generations = 30, probability of cross-over = 0.5 and probability of mutation = 1 / (number of features).

For the evaluation of the performance of classification models, the overall classification accuracy and the Kappa coefficient are used. Kappa values are helpful when there is an imbalance in the number of instances between the classes [42], which is the case in our dataset. In case of individual species classes, precision and recall values were measured. Precision is calculated as True Positive / (True Positive + False Positive), whereas recall is defined as True Positive / (True Positive + False Negative).

Results

Contrasting morphology and movement features

The individual confusion matrices shown in Fig 2, as well as the overall accuracy and kappa values for different models (shown below the confusion matrices), allow to contrast movement and morphology features. The baseline *Morphology* model is quite successful in classifying most of the species, except for *Blepharisma*, *C. campylum* and *P. aurelia* which have low recall and precision values in both SVM and DT cases (Fig 2a). Overall, the *Morphology* model based on SVM reaches a classification accuracy of 86% and Kappa value of 0.82, which is comparable to the result of the decision tree with an accuracy of 85% and Kappa of 0.81 (Fig 2a). In contrast, classification accuracy based on the MP only model had a considerably lower accuracy of 70% and Kappa value of 0.61 (SVM), and 59% and Kappa of 0.44 (DT) than the baseline morphology only model (Fig 2b). Adding ApEn features led to a small increase using SVM, whereas classification accuracy of the DT slightly decreased (Fig 2c). Further adding wavelet features led to further classification improvement for both classification methods (Fig 2d). The combination of simple aggregate movement features and morphology improved the accuracy by 8% for both classifiers (Kappa 0.92 and 0.9 for SVM and DT, respectively) compared to the morphology only baseline. (Fig 2e). Importantly, the final classification model, which integrates both morphological and all movement features, resulted in similar performances of both classifiers: 95% classification accuracy and Kappa of 0.94 in case of SVM, and 94% accuracy and Kappa of 0.93 for DT (Fig 2f). Whereas the increase due to wavelet and ApEn features in addition to simple MPs looks small with only about 1–2% overall, species-specific improvements (especially for underrepresented species like *Blepharisma* and *P. aurelia*) in accuracy and recall may justify the inclusion of advanced features such as wavelets (Fig 2e and 2f). Although DT performed generally less well than SVM for all movement-based features, once morphological features were integrated it performed as well as SVM. Although the two classification methods used different numbers of features (29 vs. 43 for SVM and DT, respectively) to reach such similar classification success, individual features from all feature sets were used in both cases, highlighting the complementary information content in each feature set (Table 1).

In order to compare the performance of different models to the morphology baseline, we looked at the difference in the overall classification accuracy and Kappa values between particular movement feature sets and morphology (Fig 3). The movement-based features, on their own, were inferior in both accuracy and Kappa compared to the baseline. However, there is an improvement compared to the baseline once complementary features sets are added to the classification model. When morphology and all movement features were integrated, the reported classification accuracy (9%) and Kappa coefficients (0.12) improved substantially, for both SVM and DT, compared to morphology only.

Species classification based on movement features alone

As classification of ciliate species based on movement features is relatively uncommon in the literature, we here compare the models based on movement features only, which would be useful if no information on morphology is available, or the morphology information is unreliable. Classification based on these sets of movement features revealed that certain features perform better than others when classifying species (Fig 4). Unsurprisingly, ApEn and the wavelet features alone were less successful in predicting species compared to the MP features, as they only characterize specific aspects of movement. However, once integrated with MP features, they increased the classification performance in almost all cases. Three species (i.e., *Cyclidium*, *Tetrahymena* and *Loxocephalus*) were quite well predicted by movement features alone, regardless of the classification method, whereas two classes (i.e., *Blepharisma* and *P. aurelia*) failed to be correctly predicted by any of the movement feature sets alone (Fig 4). Advanced movement features seem most important for *Colpidium striatum* and *C. campylum*, although the performance increase is only subtle when only movement features are considered. However, overall

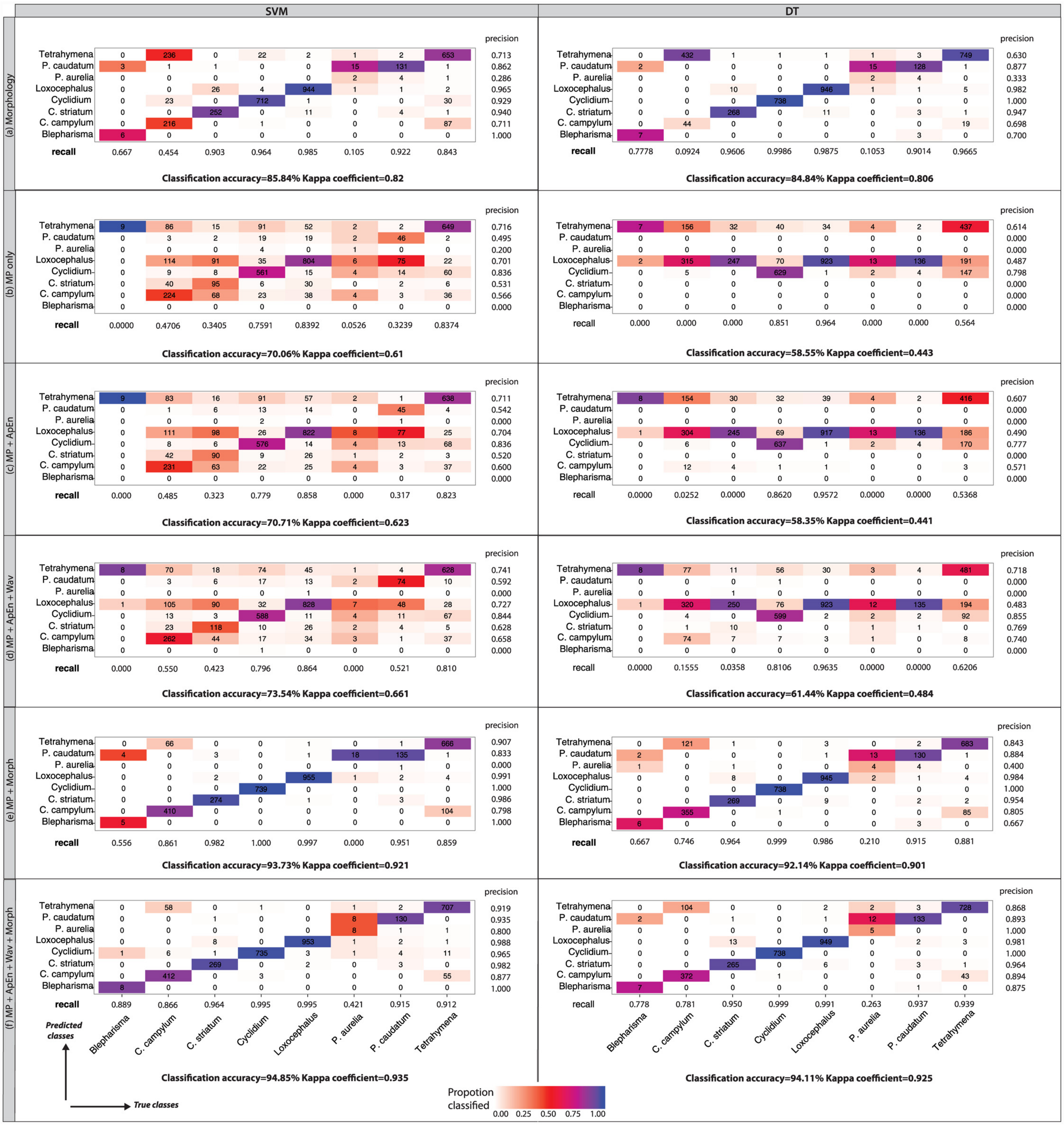

Fig 2. Confusion matrices obtained from SVM (left) and DT (right) by using different feature sets (sections a-f). The classification precision and recall values are shown for each class in all the tables. The cells are colored in order to indicate the classification precision for each class. Overall classification accuracy and Kappa values are shown below each confusion matrix. Although SVM generally outperforms DT, once both movement and morphology features are integrated, the results are very much comparable (section e and f).

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Table 1. Number of selected features using SVM and DT in the final classification stage.

	Feature sets				
Models	**MP (out of 21)**	**ApEn (out of 7)**	**Wavelet (out of 30)**	**Morphology (out of 12)**	**Total (out of 70)**
SVM	11	3	9	6	29
DT	10	5	20	8	43

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there is a steady improvement in the performance of both classifiers when movement features are added.

Discussion

Our results demonstrate that: 1) although classification models based only on movement features do not perform as well as morphological features, the integration of both feature sets results in better classification performance than each set alone; 2) adding movement features that are complementary to simple MPs aggregated on the trajectory level increases the classification success overall only slightly, although their contribution can be important for particular

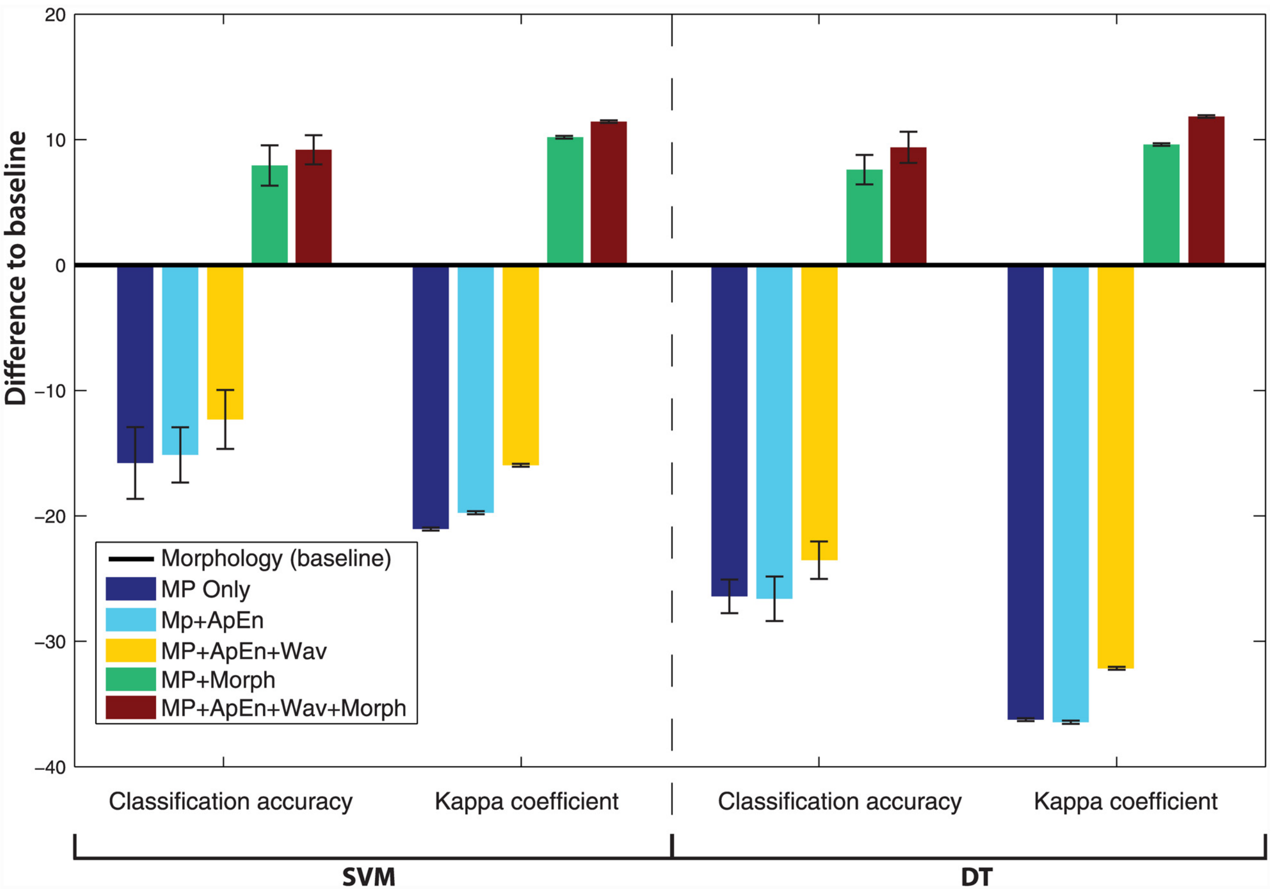

Fig 3. Comparison of the overall classification accuracy and Kappa coefficient using SVM and DT. Kappa values are scaled from [0–1] to [0–100], in order to make them comparable with accuracy values. The morphological model is considered as the baseline (0 on the Y axis) and the deviation of models using different feature sets are compared (model—baseline). The error bars shown for each bar plot are derived from the different folds of the cross validation and assist to judge the significance of the increase. Classification based on movement features fares less well than morphology alone, but once integrated, movement features increase both the classification accuracy and Kappa coefficient by about 10%.

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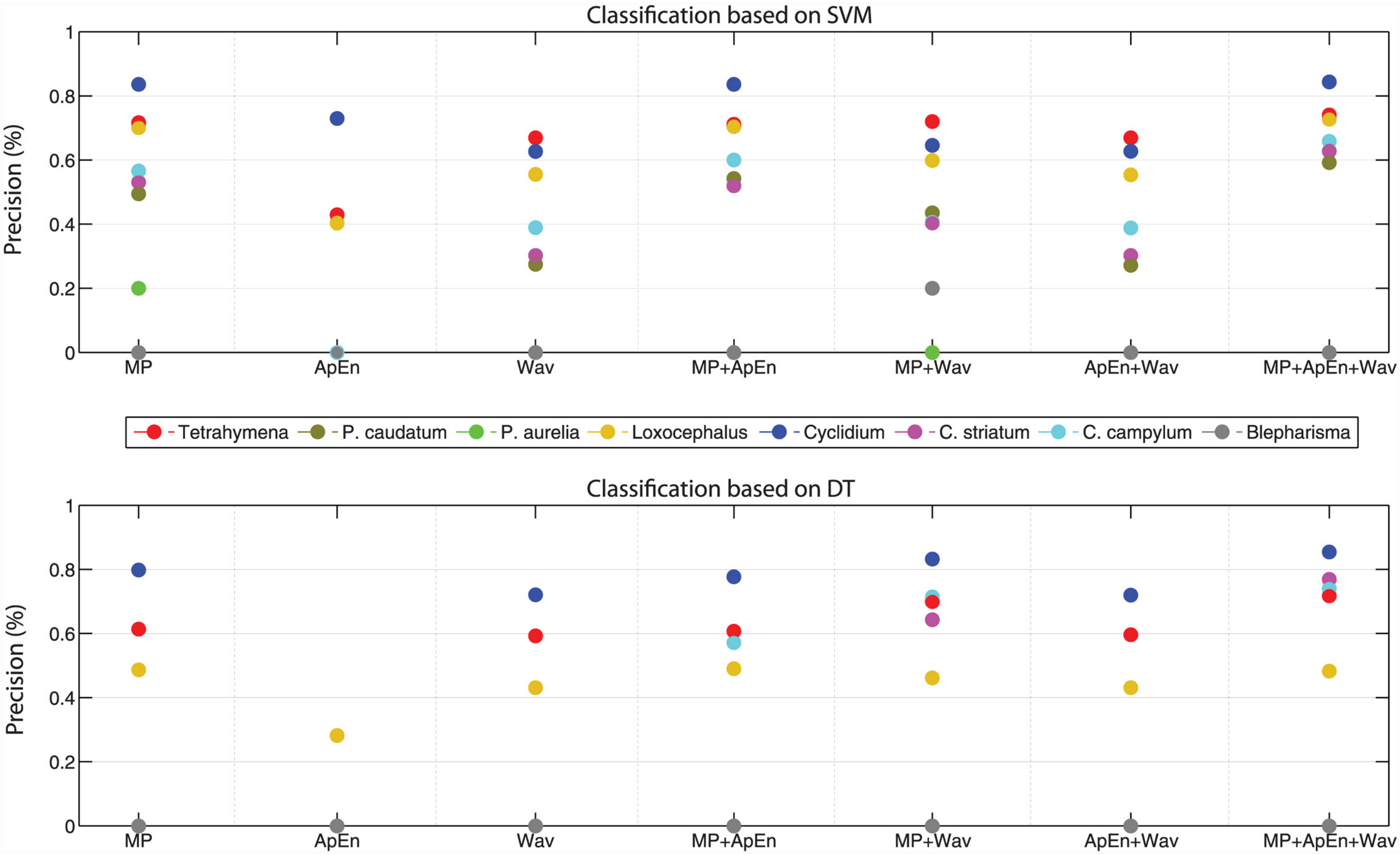

Fig 4. Precision values of predicted ciliate species based on different movement feature sets. MP is based on 21 general movement features, ApEn are the 7 ApEn features and Wav is based on 30 wavelet features. For the overlapping cases (e.g. when the precision values are zero), only the dots for one class (e.g. *Blepharisma* in grey) are shown.

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classes (especially underrepresented species in the case study here) and may vary with the classifier used; 3) once feature sets are integrated, performance of different classification methods (i.e. SVM or DT) are comparable and allow accurate and robust classification.

Classification performance based on the *MP only* model is comparable to classification based on morphology in other studies. For instance, a study looking at the automated classification of cichlid fish from Lake Malawi classified on average about 78% correctly [43], whereas another study comparing functional groups of plankton classified about 82% correctly [44]. It should be noted, however, that the numbers of classes were higher (12 combinations of species and sex in the former and 53 functional groups in the latter) in these two studies than in our case. Another study aiming for classification of 6 different movement classes of fish (i.e. a lower number as in our case) had an accuracy of 74% [45], comparable to our results based on movement only. This shows that movement features on their own, are a worse proxy than morphology for species classification in our particular case, but may still provide a worthwhile information gain in other systems, especially when automated classification outperforms human observers [43]. A possible explanation for movement being a less good predictor on its own, is the inherent variability of movement compared to morphology, which may only vary in the restricted range of morphological development. It is known for instance that phenotypic plasticity is larger for behavioral traits (which would include movement) than for instance morphological traits, as shown in a study by [46]. What would be fruitful avenues to improve species classification based on movement behavior? The temporal scale covered by our case study (20 seconds) is still relatively small compared to the lifetime of a cell (several hours to a day) and potentially the temporal scale of behavior. Hence, if we capture only a fraction of the actual behavioral mode, it may be difficult to characterize the species with that information because species identity and behavioral mode may be confounded. A study looking at the movement behavior of cows has shown that the temporal resolution and length of the trajectory determined whether behaviors could be reliably detected or not [47]. Increasing the overall length of the trajectory may help in better capturing the characteristic features of ciliate movement and hence its classification. In addition, the frequency and composition of behavioral modes expressed during the lifetime of a cell may have higher predictive power regarding species identity, as species may show specific signatures of behavioral modes when compared to each other. It was, for instance, shown that movement behavior does vary over the lifetime of cells, although most of the variation can still be summarized in two major behavioral modes [48]. It has to be noted, however, that longer videos have increasing demands in processing power and storage, which may only be justified when higher resolution in terms of behavioral modes is desired and classification success has to exceed the already high success rate shown in our study.

Slight classification performance improvements when features based on ApEn were added to the *MP only* model might be due to the fact that in the dataset used, dominant fluctuations or regularities are not really present, or that these are similar among classes. The movement of different ciliate species is rather similar to each other (as can be seen in the results of the *MP only* model) and detecting any dominant regularity in the MP values (captured through ApEn) is rather difficult in our case. One reason for the strongly converging movement behavior among species may be the shared foraging mode. The 8 ciliate species used are all bacterivorous species feeding by phagocytosis, i.e. the engulfing of food particles such as bacteria during swimming [49]. Because they share similar bacterial prey, natural selection may have led to the evolution of very similar movement strategies that allow similar foraging success among species. Although the ApEn features were not largely contributing to classification success, they still yielded a slight improvement to the classification in the case of SVM. Thus, we retained ApEn features in the classification to test if they were considered in the final feature selection process.

The third classification model including wavelet features further improved classification success. This shows that the wavelet features have been successful in capturing periodic movements in ciliate trajectories. These periodic patterns in at least some of the ciliate species could, for instance, be due to a looping behavior, where individuals move away from their departure point and return within a given time period [50]. Such a movement pattern would lead to periodic changes in the net displacement. It is most likely that these movements are performed on a small spatial scale such that they were captured by the wavelet analysis. In other applications such as the classification of EEG signals, wavelet analysis has been successfully applied, owing precisely to the periodic nature of the signals [41,51]. Our study shows that wavelet analysis provides complementary information to static movement parameters and hence improves classification success by capturing an additional aspect of movement. Importantly, adding the complementary wavelets and ApEn also improved the overall classification success from 89% using static movement parameters and morphology to 95% in this study [23]. However, as shown in Fig 4 wavelet or ApEn features on their own are less meaningful in movement based classification problems, since they will only capture specific aspects of movement such as periodic patterns.

Contrasting the morphology + MP model with the morphology + MP + advanced movement features model shows that the advanced features have merit in terms of improving species-specific accuracy and recall. Both species with the lowest number of cases (*Blepharisma* and *P*. *aurelia*) had improved accuracy and recall and even the abundant *Tetrahymena* was better classified. The increased effort of calculating advanced movement features hence pays off due to the improvements, but simple movement metrics may be preferred if the movement expressed does not show temporal structure (as for other species such as *Colpidium*, *Cyclidium* and *Loxocephalus*). Interestingly, the advanced movement features contribute only to improved classification in the case of these species, when combined with morphology, as classification only based on movement failed completely. This suggests that combined features can have synergistic effects on classification performance and the right combination of features is key for a successful overall classification.

Another achievement of this study is demonstrated by the results of the final classification model that integrates all the movement and morphology features: Careful selection of input features to obtain a set of features that collectively capture the varied aspects of movement will result in the highest classification performance, regardless of the classification method used. In this study, two classification methods with different theoretical background were employed (i.e. SVM and DT). While we were not comparing the performance of those methods, we would like to point out that selecting relevant movement features capturing different aspects of movement is of utmost importance. Such a classification approach can ensure reliable results, as can be seen through the comparable sets of selected features for building the SVM and DT models. This also could be seen in the range of selected features shown in Table 1, where SVM achieves similar results with fewer features. In the *MP only* model, all the movement parameters are used for both DT and SVM models. In the case of ApEn, SVM uses only 3 features (ApEn of distance travelled, acceleration and turning angle), compared to 5 used by DT (distance travelled, acceleration, speed, meandering and sinuosity). The selected features based on the wavelet transform show that features corresponding to different approximations and sub-bands are intermittently used, confirming the importance of both of these sub-bands in the classification. Although the two sets of selected features for SVM and DT are not exactly the same, all the developed groups of movement features showed up in the feature selection process, indicating their contribution to classifying between species. This is in accordance with the findings of other studies [26], where different combinations of features may end up in comparable results. The final message is that the combination of relevant features—movement and morphology in our case study—can ultimately build reliable classification models with high precision and recall.

Previous classification based on random forest classification showed that imbalance in the abundance of classes would influence the outcome for specific pairs of species. For instance, *P*. *aurelia* being less abundant than *P*. *caudatum* would get completely lumped into *P*. *caudatum* [23]. Whereas not unexpected due to the working principle of the random forest algorithm, the classification is unreliable for the minority class. Here we show that other classification methods such as SVM can accommodate for such imbalances better and may therefore be better suited when dealing with datasets that show large imbalances as the one used in this study.

We also employed the approach presented in [26], where a moving window of different (temporal) sizes is employed for the computation of MPs and then imported to the classification model. The results of this simple cross-scale analysis method, although not presented here, suggested that the original temporal granularity at which the data was captured was the most reliable temporal scale for the calculation of MPs. Consequently, when we employed wavelet analysis, we saw that adding features based on the DWT indeed contributed to improving the performance of the classification. We conclude from this that since scale issues manifest themselves in different ways in movement analysis, appropriate methods need to be used in order to provide complementary measures to scale-specific techniques.

As part of future work, the capability of the discrete wavelet transform will be investigated in other relevant problems in movement research, including trajectory segmentation. Movement classification and segmentation share common characteristics, given that they both aim at grouping parts of trajectories with respect to the similarity in movement properties. Due to similar conceptual backgrounds, the features extracted from movement trajectories can be used towards both classification and segmentation. Hence, features developed for the classification of entire trajectories could also be applied to subtrajectories, with little modification. The focus in the case of segmentation is to divide the trajectories into segments (subtrajectories) with homogeneous movement characteristics, which can point out the particular behaviors to be mined from movement trajectories. Since DWT decomposes the input signals at different levels, it can be used to investigate the variation of behaviors across different scales. This can be particularly interesting in different application domains, where sophisticated methods are needed to automate the process of segmenting large volumes of movement data.

Conclusions

In this study, the contribution of different movement features in a classification problem was investigated. Different ciliate species were considered as the target classes, to assess whether features based on movement can be employed as a complementary proxy to morphology in the classification problem. Our results demonstrate the value of exploring wavelet analysis, together with general movement features, in order to better distinguish the ciliate species. Such features have not been used yet in studies related to automated classification of species in the context of video analysis, and are so far rarely employed for feature extraction in movement classification studies in general. We believe that our findings are applicable to movement ecology studies in general, since they show that movement paths can be automatically classified according to classes such as species, but may also be useful to infer biological states such as behavioral modes. Our results also have potential application for instance in the field of automated monitoring of waste water.

Supporting Information

S1 Fig. Working principle of the discrete wavelet transform.
(EPS)

S2 Fig. Decomposition of the movement parameter profile through wavelet analysis at different levels.
(EPS)

S1 Text. Movement classification by the discrete wavelet transform.
(DOCX)

Author Contributions

Conceived and designed the experiments: AS FP OLP RW. Performed the experiments: FP. Analyzed the data: AS FP. Contributed reagents/materials/analysis tools: AS FP OLP RW. Wrote the paper: AS FP OLP RW.

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Supplementary Information
(PLoS ONE paper)

S1 Text. Movement classification by the discrete wavelet transform

To our knowledge, the discrete wavelet transform (DWT) has rarely been used in movement analysis, but has been successfully applied in classification problems such as the context of EEG signal classification [1,2] or image compression [3,4]. One ecological example is the work by [5], where change points were detected to segment animal movement trajectories. The value of the wavelet transform lies in the decomposition of the original movement parameter profile into multiple levels allowing the quantification of periodic characteristics of movement across different scales.

Overview of the wavelet transform

Wavelet analysis is a time-frequency representation of a signal, providing a better time and frequency resolution compared to the short-time Fourier transform (STFT). By varying the time-frequency aspect ratio, good frequency localization at low frequencies (i.e. long time windows), and good time localization at high frequencies (i.e. short time windows) are achieved [3,6]. The wavelet transform (WT) is the process of expressing an input signal through a set of functions, by shifting and dilating a single function called the mother wavelet function. This makes it possible to decompose the input signal at different scales, leading to a set of coefficients at each level called wavelet coefficients.

Two forms of WT are possible: the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT). For our purpose of generating input features for a classification model, the CWT will generate an excessive amount of data, which cannot easily be aggregated and fed into the classification model. In contrast, the DWT is similarly accurate as the CWT [3] and further analysis of the wavelet coefficients is done by summarizing the coefficients of different decomposition levels as input features for the classification. In the following, we will focus exclusively on the DWT.

Using the DWT, the signal S is successively decomposed into multiple levels of resolution (S1 Fig). This decomposition procedure yields multiple approximations and detail information by passing through low-pass and high-pass filters, respectively. The low-pass filter keeps only the frequencies lower than a certain threshold, leading to maintain the general structure of the signal. Whereas high-pass filter allows passing signals with frequencies higher than the threshold, allowing to capture details of variation in the signal. The decomposition involves subsampling of the original signal at dyadic scales, $x = 2^j$ (with $j = 1, 2, \ldots, k$ levels). The original signal then can be calculated as the summation of approximations A_j and details D_j.

S1 Fig. Working principle of the discrete wavelet transform. *$S = A_j + j * D_j$, where A_j represents the approximation at the final level of decomposition and D_j represents the corresponding detail. h[n] is the high-pass filter and l[n] is the low-pass filter.*

Summarizing the extracted information is required to use it as input features in the classification. In the discrete wavelet transform, this may be accomplished by summarizing the wavelet coefficients.

Application of the discrete wavelet transform to ciliate movement trajectories

In the feature extraction step, all the approximations A1 .. An and the details D1 .. Dn of the MP signals were considered. The importance of the approximation sub-bands lead us to integrate all the features based on them. The approximation component captures the general structure of the signal and the detail component is able to capture the variations in the signal. These two sets of information are adequate to reconstruct any input signal [3,6]. Therefore, in most of the studies using the DWT, the moment statistics of these components are used as the input features [2]. However, the selection of the sub-bands from which the features are extracted depends on the patterns that are to be mined from the data. For example, in [5], the main interest was to pinpoint the change points in the movement and this information lies in the high-frequency component of the signal, hence the required information could be obtained by merely looking at the sub-bands. However, in our classification problem the behavioral patterns that form the movement classes manifest themselves in intervals that cover a certain time period and thus affect the general structure of the signal. Therefore, we used the approximation together with the detail components in order to investigate the movement classes.

Three summary statistics were computed for each sub-band and considered as input features for the classification. These include the mean of the absolute values of the coefficients in each sub-band; average power of the wavelet coefficients in each sub-band; and standard deviation of the coefficients in each sub-band.

This approach also helped in selecting the appropriate number of decomposition levels in the wavelet analysis, since it is an important factor in the analysis of signals using the DWT. In the literature, the number of decomposition levels has been decided based on the dominant frequency components of the signal, such that those parts of the signal that correlate well with the frequencies necessary for classification of the signal are retained in the wavelet coefficients [2]. According to [5], the DWT eliminates noise at the 1st and 2nd level of decomposition and the discontinuity in the signal becomes visible at the 4th or 5th decomposition. Our findings are in agreement with these observations, as most of the information needed for the reconstruction of the signal is retained quite well up to the 5th level of decomposition (S2 Fig).

S2 Fig. Decomposition of the movement parameter profile through wavelet analysis at different levels. *The approximation and detail sub-bands as well as the obtained wavelet coefficients are shown for each level.*

For the mother wavelet function, as another deciding factor in the wavelet analysis, different functions were assessed in order to determine their effect on the classification performance. A Daubechies wavelet was chosen, due to its superior performance, and order 4 selected to detect the discontinuities in the signals.

Among the MP profiles employed in this study, the distance travelled and speed are the most commonly used parameters in conjunction with the wavelet analysis in the literature [5,7,8]. For both, periodic patterns in the profile may be expected whereas for other parameters, it would be rather difficult to interpret the meaningfulness of periodic patterns in their profiles. Classification experiments that we conducted solely using wavelet-based features supported the findings from the literature: superior results could only be obtained using one of these two parameters. In the experiments reported here, we used the profiles of the distance travelled to extract the wavelet-based features.

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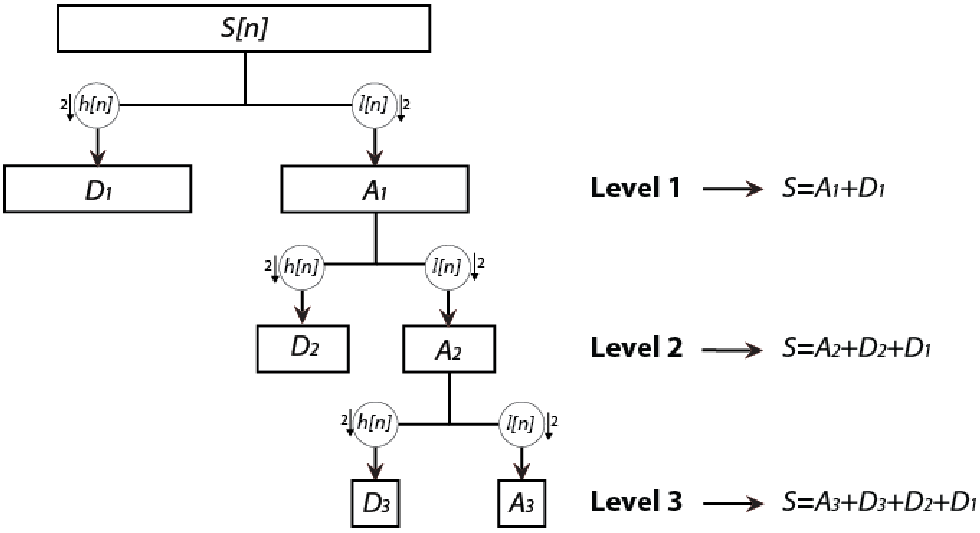
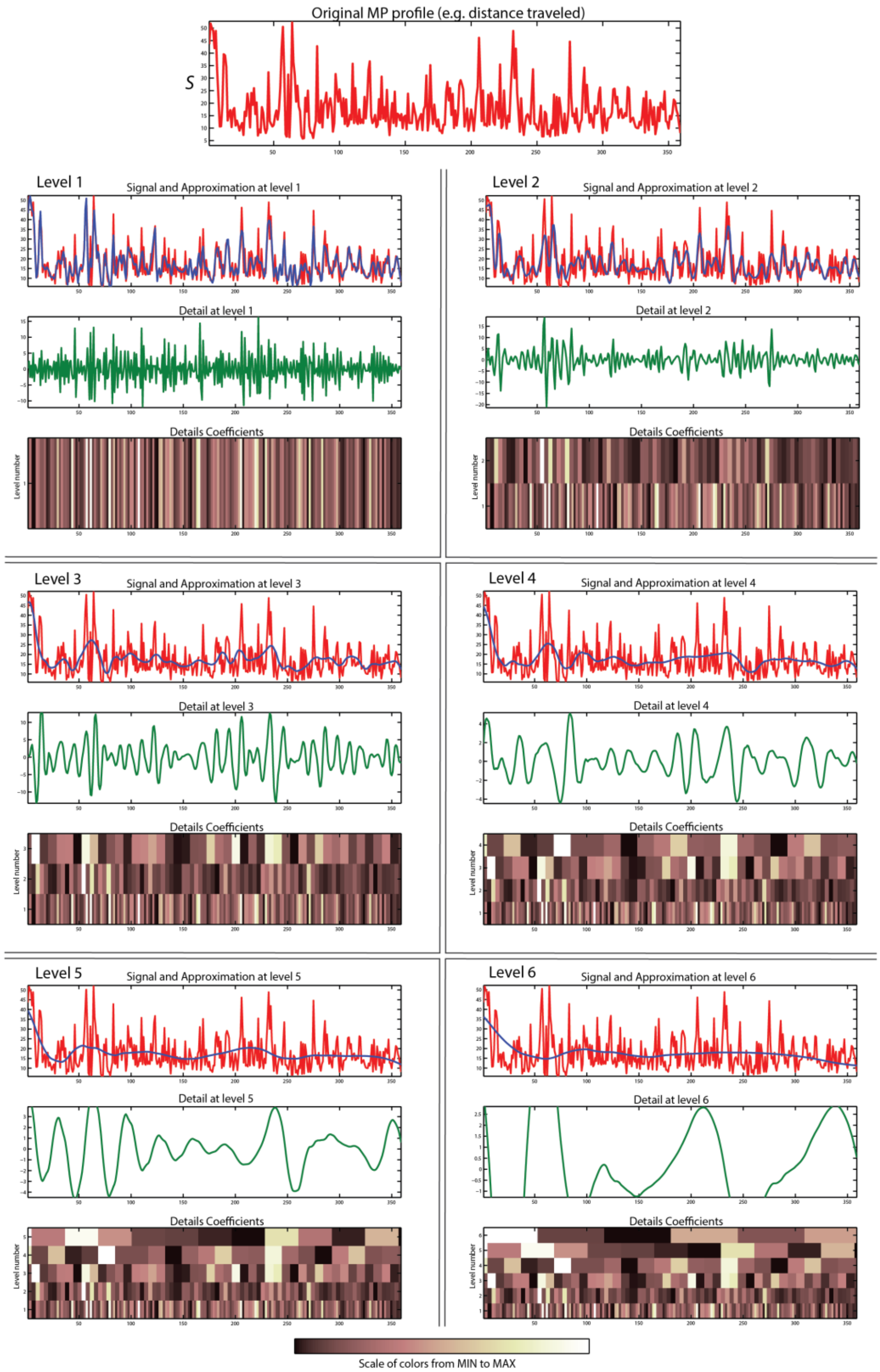


S1 Fig. Working principle of the discrete wavelet transform. *$S = A_j + j * D_j$, where A_j represents the approximation at the final level of decomposition and D_j represents the corresponding detail. h[n] is the high-pass filter and l[n] is the low-pass filter.*



S2 Fig. Decomposition of the movement parameter profile through wavelet analysis at different levels. *The approximation and detail sub-bands as well as the obtained wavelet coefficients are shown for each level.*

Chapter

5

Characterizing change points and continuous transitions in movement behaviors using wavelet decomposition

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Other items: 3 Tables, 6 Figures, 8 Supplementary Information

Summary

1. Individual behavior, i.e. the reaction of an organism to internal state, conspecifics and individuals of other species as well as the environment, is a crucial building block of their ecology. Modern tracking techniques produce high-frequency observations of spatial positions of animals and accompanying speed and linearity measurements. However, inferring behavioral modes from movement trajectories remains a challenge.

2. Changes in behavioral modes occur at different temporal and spatial scales and may take two forms: abrupt, representing distinct change points; or continuous, representing smooth transitions in movement modes. The multi-scale nature of these behavioral changes necessitates development of methods that can pinpoint behavioral states across spatial and temporal scales.

3. We propose a novel segmentation method based on the discrete wavelet transform (DWT), where the movement signal is decomposed into low frequency approximation and high-frequency detail sub-bands to screen for behavioral changes at multiple scales. Approximation sub-bands characterize broad changes by taking the continuous variations between behavioral modes into account, whereas detail sub-bands are employed to detect abrupt, finer-scale change points.

4. We tested the ability of our method to identify behavioral modes in simulated trajectories by comparing it to the state-of-the art methods from the literature. We further validated the method using an annotated dataset of turkey vultures (*Cathartes aura*) relating extracted segments to the expert knowledge of migratory versus non-migratory patterns. Our results show that the proposed DWT segmentation is more versatile than other segmentation methods as it can be applied to different movement parameters, performs better or equally well on the simulated data, and correctly identifies behavioral modes identified by the experts. It is hence a valuable addition to the toolbox of land managers and conservation practitioners to understand the behavioral patterns expressed by animals in natural and human-dominated landscapes and integrate these in effective land management plans and policies.

Keywords: movement behavior, change points, continuous transitions, scale, segmentation, discrete wavelet transform

1. Introduction

The behavior can be defined as the response of an individual to its internal state, interactions with conspecifics or individuals of other species, or its environment. For a long time, behavioral observations relied mainly on visual descriptions and hence were limited in the number of individuals that could be monitored as well as the temporal and spatial scales of observations (Kühl & Burghardt 2013). The rise of modern tracking techniques has substantially changed the situation and nowadays animals can be followed with unprecedented spatial and temporal precision (Cagnacci et al. 2010). However, as careful annotations by visual observation are rarely available for long-term trajectories nowadays, the challenge is to infer the different behavioral states from animal trajectories automatically (Gurarie et al. 2016).

Inferring behavior from movement trajectories can be hampered by behavioral heterogeneity, which is a key property of movement processes and results in multiple movement modes in the trajectory of an individual (Gurarie, Andrews & Laidre 2009). For example, the behavior of an animal is influenced by environmental heterogeneity such as varying spatial and temporal resources (Giuggioli & Bartumeus 2010; Yackulic et al. 2011). Animals therefore usually linger (i.e. move slowly and with short steps and large turning angles) in locations with abundant resources, whereas they move faster and more linear in locations without resources or when migrating (Schtickzelle et al. 2007). Moreover, due to the effect of internal and external factors influencing the movement at different spatial and temporal scales, behaviors may result in compounds of different patterns at various scales (Nathan et al. 2008; Thiebault & Tremblay 2013). Confining the analysis of scale to the original temporal granularity will hence overlook the fact that each movement pattern has a particular scale range at which it is manifested (Laube & Purves 2011; Soleymani et al. 2014; de Weerd et al. 2015). Importantly, not only the behavioral modes but also the transitions between them are intrinsically multi-scale (Gaucherel 2011). For example, different behaviors along a bird trajectory (i.e. flying, foraging, resting) may occur at different spatial and temporal scales and similarly, the magnitude of variations in a flying mode are at a different scale than the ones in a resting mode. Thus, extracting behavioral states from movement data requires an analysis approach that can act at multiple temporal scales, in which not only the abrupt changes are detected, but also the continuous variations in movement characteristics are investigated.

Trajectory segmentation represents a set of methods, where variation in movement parameters (MP) — such as speed, tortuosity, etc. — is used to identify segments of homogenous characteristics corresponding to particular behavioral states (Buchin et al. 2011). Different segmentation approaches have been employed to identify behaviors in movement trajectories of a range of species. The first approaches were based on simple metrics such as fractal dimension (Fritz, Said & Weimerskirch 2003; Nams 2005; Webb et al. 2009) or first-passage time (Fauchald & Tveraa 2003; Pinaud 2008), which can pinpoint different regimes in the movement signal. These methods, however, do not identify change points or segments. More recently, Gurarie, Andrews & Laidre (2009) developed a method for behavioral change point analysis (BCPA) based on likelihood estimation to detect abrupt structural changes in the values of movement parameters. Thiebault & Tremblay (2013) introduced another segmentation method based on the consistency of speed and direction in movement to split trajectories based on breakpoints that correspond to decisions of animals to change their movement. Machine learning approaches have also gained traction: de Weerd et al. (2015) used decision trees to classify high-frequency movement trajectories of cows into fine-grained behaviors of foraging, lying, standing and walking. Finally, the most mechanistic but also technically demanding segmentation approaches are Bayesian state-space models, which were shown to correctly classify turning angle and step-length distributions into different behavioral modes (Beyer et al. 2013). Besides being computationally demanding and hence being inappropriate for large-scale analyses, Gurarie et al. (2016) illustrate two important limitations of those methods for behavioral characterization of movement data. The above approaches all rely on a single, specific movement parameter (e.g. speed) to detect changes in behaviors. Therefore, they generally have difficulties identifying cases where behavioral states are affecting other parameters (e.g. linearity), a problem termed *model misspecification* by Gurarie et al. (2016). Model misspecification extends to methods that do not account for autocorrelation in the movement variables, leading to spurious change points and hence false inference. Overlooking autocorrelation effects will also cause methods to fail in correctly *determining the magnitude of changes* in movement modes, which is due to their emphasis on detecting abrupt changes and therefore missing the continuous variations in the movement modes (Gurarie et al. 2016).

Recognizing the importance of scale, some of the aforementioned methods are capable of multi-scale analysis (i.e. fractal analysis and first-passage time). There are other methodological approaches for computation of MPs at different temporal window sizes (Laube & Purves 2011) or the multi-scale straightness index (Postlethwaite, Brown & Dennis

2012). The wavelet transform has been proposed as another multi-scale approach to link movement patterns (periodic movements) to internal and external factors (e.g. physiological, ecological, contextual; Wittemyer et al. 2008). Polansky et al. (2010) used the continuous wavelet transform (CTW) to identify temporal dependency (i.e. timing and extension) of behavioral patterns, which are not detected by other methods (e.g. Fourier transform). Gaucherel (2011) identified the continuity between transitions of discrete behavioral modes using CWT analysis. Puckett, Ni & Ouellette (2015) employed CWT to extract behavioral modes indicating pairwise interactions in trajectories of swarming midges. The discrete wavelet transform (DWT) on the other hand has been applied in change point detection of bird trajectories (Sur et al. 2014) and to extract recurring and periodic behaviors of ciliates (Soleymani et al. 2015). CWT is mainly used where a qualitative explanation of movement behaviors is sought by visual exploration of the wavelet coefficients, whereas DWT provides a quantitative approach readily streamlined for change point detection in movement behavior.

We propose a new segmentation method based on the discrete wavelet transform to infer behavioral states form movement trajectories in a multi-scale manner. Implementation of the method in *Matlab R2016a* scripts are provided as online supplementary materials. In DWT, the movement signal (formed by the time series of a movement parameter) is decomposed into *low-frequency approximation sub-bands* and *high-frequency detail sub-bands* at different (scale) levels. In case of approximation sub-bands, a method based on peak analysis is used to detect broad-scale patterns, whereas in the case of detail sub-bands, thresholding of DWT coefficients is used to identify abrupt change points. To our knowledge, no study so far combined information from detail and approximation components of the DWT for behavioral movement analysis.

We compare the performance of DWT to state-of-the-art methodological approaches such as first passage time (FPT), Bayesian partitioning of Markov models (BPMM) and behavioral change point analysis (BCPA) evaluated in detail by a recent study (Gurarie et al. 2016), showing how the DWT-based segmentation can overcome limitations of these methods. We validate our method by applying it to long trajectories of migratory turkey vultures (*Cathartes aura*) that are manually annotated by experts to distinguish between different migration stages. The results show high correspondence of these annotations with the segments identified by the DWT.

2. Materials and Methods

2.1 Wavelet analysis

Wavelet analysis is a method for multi-resolution time-frequency representation of a signal. The wavelet transform is the process of expressing an input signal, by dilating and contracting a single function, using a mother wavelet function shifted across the signal. A set of wavelet coefficients are used to represent the input signal at different scales, providing a more efficient representation (by employing fewer coefficients) compared to the short-time Fourier transform (Daubechies 1990).

There are two main types of wavelet transform: the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT). While the CWT calculates the coefficients at every possible scale, the DWT chooses only a subset of scales and sampling positions through dyadic positioning and scales, $x = 2^j$ (with $j = 1, 2, \ldots, k$ levels). Nevertheless, it is considered to be just as accurate as the CWT (Mallat 1999; Khorrami & Moavenian 2010). During the decomposition process in DWT, the original signal S is passed through low-pass and high-pass filters, yielding multiple approximation (A) and detail (D) coefficients, respectively. Since the low-pass filters retain only the frequencies lower than a certain threshold, the general structure of the signal is maintained. Conversely, the high-pass filters allow signals with frequencies higher than the threshold to pass, thus enabling to capture the details of variation in the signal.

We skipped the down-sampling stage and instead used the wavelet *sub-bands* (Appendix S1). This was done to retain the length of the sub-bands at all decomposition levels the same as the length of the original signal, allowing for investigating the variation of patterns across different scales (i.e. decomposition levels).

2.2 DWT-based segmentation method

First, MPs are computed for each trajectory fix (x, y, t) from raw movement data, representing the input signal for the wavelet analysis (e.g. the profile of speed over time). Through the decomposition of the MP profile, the uncertainty in frequency is reduced by two and the resolution of the frequency is doubled (Gokhale & Khanduja 2010; Sur et al. 2014). We selected a *Daubechies* wavelet of degree 4 as the mother wavelet, due to its superior performance in detecting discontinuities and changes in the signal (Subasi 2007; Sur et al.

2014). We first show how the smoothed signal obtained by the approximation sub-bands will lead to coherent broader-scale segments and then extend the analysis to the detail sub-bands, which can be used to detect more fine-scale change points.

2.3 Peak analysis of approximation sub-bands

The incentive for using the approximation sub-bands is due to the locally adaptive property of DWT, where by accounting for the values of neighboring fixes, the effect of frequency localization becomes stronger at deeper level of decomposition and therefore the signal gets smoother (Daubechies 1990; Mallat 1999). By using this multi-scale representation, a decomposition level is consequently reached where the signal can be divided into distinct segments. Peak analysis is performed in order to differentiate between such segments, by using the *height* (black vertical bars in Fig. 1b) and the *width* (orange horizontal bars in Fig. 1b) of the resulting peaks at different levels. The height is the peak value (i.e. distance to the baseline). To determine the width of the peak, the peak *prominence* (red vertical bars in Fig. 1b) is used. The prominence of a peak is the minimum vertical distance to the local minima on either side of the peak, before reaching a higher peak or the signal endpoints. The width is then computed as the distance between two points on either side of the peak where the signal intercepts the horizontal line through the midpoint of the prominence.

Peak analysis has been widely used in different areas including genomic data analysis (Wilbanks & Facciotti 2010; Hocking, Hocking & Mcgill 2015) and moment segmentation of heart sound patterns (Sun et al. 2014). In this study, peak *height* is used to distinguish between behavioral phases and the peak *width* indicates the magnitude of the segments. Therefore, the segmentation problem will be transformed into a peak analysis problem by looking into the behaviors of peaks at different decomposition levels. The combination of height and width enables us to identify behavioral segments: First a decomposition level is selected where the segments can be sufficiently distinguished. Depending on the variations in the target behaviors, the method is flexible to select the relevant approximation sub-band at different levels. Second, thresholds for the height of the peaks are used to differentiate between behaviors. A threshold can be selected to differentiate the heights of peaks A and C from peak B (Fig. 1b). Depending on the number of target behaviors, the method is flexible to incorporate multiple behavioral phases by employing multiple thresholds for the heights of the peaks. The segmentation algorithm is designed such that all the adjacent peaks below a certain threshold will represent the same segment and a new segment is only started if the adjacent peak exceeds the threshold. The magnitude of the segment is then calculated by summation of all the peaks within a threshold range. More detail on the setting these parameters is given in the parameterization section below.

2.4 Thresholding of the detail sub-bands

In contrast to the approximation sub-bands (*A*), the frequency resolution of the signal becomes more precise at each level of decomposition in the detail sub-bands (*D*) and is therefore more likely to show abrupt change points. Segmentation based on detail sub-bands only is similar to the method by Sur et al. (2014), but while they assumed a normal distribution of Z-scores of the detail coefficients (an assumption that often does not hold), we do not make any assumption about the distribution of the data. Instead, we first apply a threshold to the values of the detail coefficients and then concatenate the segments shorter than a specified length.

The value of the threshold is decided based on the abrupt changes in the detail coefficients. Same as the approximation sub-bands, first a decomposition level in the detail sub-bands is selected where discontinuities in the signal become evident and therefore suggestive of distinct behavioral modes. The change points are then detected by measuring the first derivative (i.e. difference to the previous points) of the detail coefficients. The instances exceeding the difference to the previous point higher than a certain threshold are selected as change points. In the example shown in Fig. 2, there are two dominant frequency ranges, corresponding to two behavioral modes (i.e. migration and non-migration). The points shown in red are indicating a change point, exceeding a threshold value to the preceding fix. In the parameterization section, more detail is given on the setting of these parameters.

Because of the high heterogeneity of movement data, detail sub-bands are often very variable. Using only the first derivatives of the detail sub-bands will thus result in numerous change points. In order to compensate for that, a shortest length constraint for the extracted segments is considered, concatenating all the fixes (or a collection of fixes) in-between. This will smooth the irregular variation and result in longer segments. This procedure continues until all the points and short sub-trajectories (with a length of less than the specified number of fixes) are concatenated. By changing the shortest length constraint, the sensitivity to detect fine-scale behaviors is adjusted.

2.5 Parameterizing the decomposition levels and the thresholds

For both the approximation and the detail sub-bands, the selection of appropriate decomposition level is done in a supervised manner by comparing to the known behaviors in simulated and annotated datasets. In approximation sub-bands, the decomposition level is selected as the level where the extracted segments and their lengths best match the given behaviors. The selected decomposition level will hence vary depending on the chosen movement parameter and the data used. Thresholds for the height of the peaks were selected by visual inspection but we tried to be biologically-driven, i.e. by selecting the values of lower peaks as thresholds to detect the segments of higher peaks. Similarly in the detail sub-bands, the decomposition level is selected as the level where frequency breaks best represent the behavioral changes in the data. We performed the analysis on the detail sub-bands for the Turkey Vulture dataset only, since the simulations did not contain any short-range behavioral variation by design. The change points in the detail sub-band were defined as fixes with a frequency difference greater than 1 Hz from the preceding fix.

2.6 Simulated data

We used two of the three simulations and the associated R code provided in Gurarie et al. (2016) to generate tracks with switches in the speed and the tortuosity values representing behavioral changes in movement (Appendix S2). In each simulation, one movement parameter is changing: speed in the first track (Appendix S2a); tortuosity in the second track (Appendix S2b). The behavioral modes are known in both simulations: the first and the fourth modes include 1000 fixes indicating intensive movement (i.e. low speed and high tortuosity) (shown in dark blue), whereas the second and third modes last 500 fixes representing higher speed and less tortuous tracks (shown in green). The third mode represents movement with highest speed and least tortuosity (shown in red).

To compare the performance of the DWT segmentation to the segmentation methods presented in Gurarie et al. (2016), we count the number of extracted segments on the simulated data for each of the methods (Table 2). For detailed investigations of the performance of each of these methods except the DWT, the reader is referred to Gurarie et al. (2016). We exclude the multi-state random walk (MRW) model, since it assigns behavioral states to fixes rather than segments and hence cannot be compared. Since MRW performed rather poorly compared to the other methods presented in Gurarie et al. (2016), our comparisons remain representative. Speed for the first simulation and tortuosity (product of estimated velocity and the cosine of turning angles as calculated by the BCPA) for the second simulation were generated as the relevant MP signal for wavelet analysis. The DWT segmentation was applied on the 6th level of approximation sub-bands (Appendices S3, S4).

2.7 Empirical data: Turkey vulture

We use four GPS tracks of turkey vultures (*Cathartes aura*) from the Interior North America population to illustrate the segmentation method on real data. As shown in Fig. 3, the migration path extends from Canada to South America across central regions of North America. These birds show several states during their annual migrations: (1) breeding areas in North America, (2) outbound migration in the Fall from breeding areas to wintering grounds, (3) tropical wintering grounds in South America, and (4) return migration to breeding grounds in the Spring. The data is manually classified into the above-mentioned behavioral states (four segments) by domain experts as discussed in Dodge et al. (2014). The track of one individual named *Leo* is used for setting the parameters of the DWT segmentation. For validation purposes, three trajectories of individuals *Mac*, *Steamhouse 1* and *Steamhouse 2* are used (Table 1).

We first applied the segmentation approach based on the approximation sub-bands on the speed profiles of turkey vultures to illustrate the ability to recover behavioral annotation by expert knowledge. Level 9 of the approximation sub-bands was selected for segmentation based on the data of *Leo*. The threshold for the height of the peaks was selected based on the highest peak in the non-migratory segments of the *Leo* track.

Second, by extracting detail sub-bands in addition to approximation sub-bands, DWT has the potential for detecting fine-scale behaviors. We show this by investigation of level 5 of the detail sub-bands of *Leo*. Here, we define a change point as a fix with a frequency difference greater than 1 *Hz* from its preceding fix.

3. Results

3.1 Simulated data

DWT segmentation correctly extracted the 4 behavioral phases in the first two simulations (Table 2). In the speed-switch simulation, BPMM correctly detects all the four behavioral phases, while FPT (3 segments) and BCPA (6 segments) fail to capture the intermediate transitions. In the time-switch simulation, BCPA detects all the four phases accurately, whereas FPT remains uninformative about the intermediate transitions (3 segments) and BPMM detects far too many segments (13).

3.2 Turkey Vulture data

3.2.1 Extraction of long migratory patterns using approximation sub-bands

All the annotated segments are retrieved accurately for *Leo*, except for a very short migration season at the end of the track (Fig. 4c and 4d). This is also the case for *Mac*, where a redundant segment is found on the edge (Appendix S5). This is not the case for the DWT segmentation results on *Steamhouse 2* and *Steamhouse 1*, where all the behavioral segments are correctly identified (Table 3). Appendices S5 to S7 illustrate the application of the DWT segmentation method on these tracks.

The average temporal difference in the change points between the extracted segments and annotations is ~11 days among the four individual trajectories (Fig. 5), a good precision compared to the length of migratory segments (range approx. 45 - 80 days). As expected, the differences are lowest for *Leo*, since it was used as training data. The high difference values for *Mac* might be due to highly heterogeneous and unevenly distributed migration seasons compared to the other individuals (Appendix S5). For *Steamhouse 1* and *2*, the results are overall reasonable (Appendices S6, S7). The high difference in some seasons might be due to fact that the data is sampled at a different sampling rate (3 hours) compared to the 1 hour of *Leo*.

3.2.2 Extraction of fine-scale behaviors using detail sub-bands

Considering the high level of heterogeneity in the variation of detail coefficients (Fig. 6a), the thresholding of detail coefficients results in 162 change points shown in Fig. 6b. Careful investigation of the change points has the potential of identifying behavioral states within the migratory/non-migratory phases and mine movement trajectories for cryptic behaviors.

The result of segmentation after applying the shortest length constraint (i.e. by concatenating the sub-trajectories shorter than 500 fixes between two change points) is shown in Fig. 6c. This was selected as the appropriate length for the occurrence of migratory patterns in the data. Many of the change points shown in Fig. 6b are smoothed out by the concatenation. Most of the extracted segments now largely resemble the number and position of the annotated segments. However, some interesting differences are apparent within the non-breeding grounds in the years 2009, 2010 and 2011. Although not annotated by the expert focusing on migration behaviors, these differences could reflect real fine-scale behavioral differences in the non-breeding grounds and only can be detected in the detail sub-bands.

4. Discussion

The high complexity and multi-scale nature of movement behaviors hampers the identification of homogeneous sub-trajectories indicative of behavioral modes in movement trajectories. Here we have shown that the discrete wavelet transform compares favorably against state-of-the-art methods in automatic behavioral segmentation of simulated trajectories, as well as on real movement trajectories of turkey vultures annotated by domain experts. In the following discussion, we address the specific advantages of the DWT, such as overcoming model misspecification, scalability to large numbers of trajectories and detection of multi-scale behaviors.

Circumventing the model misspecification problem

DWT proved successful in relating representation signals (i.e. the sub-bands) to multiple behavioral modes. All four behavioral segments in both simulations were precisely detected using the appropriate approximation sub-bands. The precise detection of segments in approximation sub-bands was due to their ability to take into account autocorrelation, which is a common limitation of other segmentation approaches and part of the *model misspecification* problem (Gurarie et al. 2016). However, higher levels of decomposition also result in a higher degree of autocorrelation, which may over-smooth the signal. Therefore, choosing the proper level of decomposition is crucial when applying DWT.

By choosing the relevant response variables in the two simulations (i.e. speed and tortuosity), the four modes were efficiently distinguished. This addresses the second part of the *model misspecification* problem. Since the method is not dependent on any particular movement parameter, multiple responses may be tested. In contrast, the other segmentation methods only performed well if changes in the behavioral phases were captured by the default movement parameter used for extracting behavioral states.

DWT to infer and quantify behavior from GPS trajectories

In the case of the turkey vulture data, the approximation sub-bands successfully identified the broad-scale patterns (migratory vs. non-migratory) lasting over a long time period. By emphasizing the effects of seasonal patterns, the approximation sub-bands at a certain level provide a representation that allows distinguishing the migratory patterns from non-migratory patterns. The detail sub-bands in contrast highlighted more segments in the breeding seasons of 2009, 2010 and 2011 (Fig. 6c). Although these segments are not matching the annotated data, they may be explained by larger breeding grounds in warmer seasons, where turkey vultures have to move longer distances to forage (Dodge et al. 2014). Detail sub-bands and the concatenation approach hence have the potential of detecting cryptic behavior. The extracted segments representing migration seasons were also clearly narrower than the ones from the approximation sub-bands. This touches on another point raised by Gurarie et al. (2016), which is the ability of the DWT segmentation method to precisely specify the magnitude of change in movement. Using the peak width in approximation sub-bands to describe the magnitude of change provides a direct measure that can be used in further analyses.

The application of the method on real-world trajectories and successfully recovering the behaviors identified by experts clearly illustrates the power of the DWT approach to work on noisy (see outliers in Fig. 3), partly irregular data (including gaps) and hence its use for a multitude of study systems in which such data is collected. The DWT segmentation serves as a general method to be applied on large numbers of trajectories in those domains.

However, the method is not without downsides as shown by the boundary effects in the trajectory of *Leo*. We recommend discarding segments or parts of segments affected by the "cone of influence" (Cazelles et al. 2008), or at least interpret these with great care. Another downside may be that wavelet analysis is also quite demanding in terms of sampling frequency and length of the movement profile. However, the ever increasing performance of modern GPS tags is likely to compensate for these data requirements. Another issue is the supervised approach employed, in which the parameters of the method were set using the annotated or the simulated data. In cases where no annotation is available, the method can still be used, however expert advice should be considered in the selection of parameters. Collection of ground truth data and annotation of selected trajectories is recommended for parameter setting and validation; the incurred costs may be compensated when the procedure can be applied subsequently to hundreds of trajectories.

Our method takes a single control parameter (i.e. threshold) for both the segmentation based on the approximation and the detail sub-bands, which is less or equal to the number of parameters required to tune the other segmentation methods discussed in Gurarie et al. (2016). Moreover, the parameter settings of our algorithm are biologically intuitive, which according to Gurarie et al. (2016) is an important factor when fine-tuning the analysis.

Comparison with previous work on DWT and CWT for behavioral segmentation

A similar application of DWT in trajectory segmentation was introduced by (Sur et al. 2014). In their work, the Z-scores of detail coefficients at a certain wavelet decomposition level are assumed to follow a normal distribution and thresholds are based on the 3-sigma rule. There are, however, certain limitations to this approach: 1) Z-scores may not follow the normal distribution (as was the case in our dataset); 2) thresholds based on n-sigma classes are arbitrary because they lack a link to different movement modes; 3) it is unclear how to extract more than three movement modes based on the sigma rule; 4) using only the detail sub-bands is susceptible to noise and generally leads to an excessive number of segments. Our approach in contrast, makes no hypothesis about the distribution of the wavelet coefficients and the automatic thresholding can detect more than 3 behaviors. Moreover, the full information content of the wavelet decomposition is exploited by using both approximation and detail sub-bands.

Another study by Gaucherel (2011) used the continuous wavelet transform as a powerful tool for investigating the continuous transitions between the behavioral modes. However, the CWT has limitations in inferring the processes underlying movement by building the continuous wavelet map as the summation of the details at all decomposition levels plus the approximation at the final level. Therefore, the map is highly affected by the presence of the detail components and there is also no possibility to relate different frequency bands to different target behaviors. DWT helps discriminating behavioral modes in a more quantitative manner and relating the analysis scale to the multiple scales of expressed behaviors can contribute to our understanding of movement processes across scales.

5. Conclusion

Inferring movement behaviors from trajectories is complicated by the high level of variability and the multi-scale nature of movement. We believe that the proposed segmentation method is an important step forward to extract movement behavior from movement trajectories, overcoming some of the limitations of previous methods. Methods that are flexible enough to exploit different movement parameters as well as able to pinpoint not only behavioral segments but also the smooth transitions in between are urgently needed to exploit the full information content in the increasing number of movement trajectories available. Relating movement behaviors across scales to external and internal factors of focal individuals is one of the goals of the movement ecology paradigm (Nathan et al. 2008) and the DWT has the potential to uncover some of these links.

Data accessibility

Four turkey vulture trajectories are obtained from the Movebank Data Repository (doi:10.5441/001/1.46ft1k0).

Matlab scripts and wavelet coefficients matrices are uploaded as supplementary information (Appendix S8).

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Table 1. Summary of the Turkey Vulture track.

Individual	Tracking period (from – to)	Number of fixes	Temporal resolution	Usage
Leo	16.06.2007 – 19.03.2013	35256	1 hour	Parameter setting of DWT method
Mac	17.06.2007 – 12.03.2008	11889	1 hour	Validation
Steamhouse 1	22.05.2009 – 18.03.2012	6545	3 hours	Validation
Steamhouse 2	23.05.2009 – 19.03.2013	10472	3 hours	Validation

Table 2. Number of segments extracted by DWT compared to three state-of-the-art methods presented in Gurarie et al. (2016). Only the DWT was able to extract the correct number of segments in both simulations.

Model	Speed-switch	Time-switch
FPT	3	3
BPMM	4	13
BCPA	6	4
DWT	4	4
True number of segments	4	4

Table 3. Comparison of the extracted and annotated behavioral segments for the four turkey vulture individuals. Individual Leo was used for parameter tuning and validation, the remaining individuals for external validation.

Track	N. of annotated segments	N. of extracted segments	Remarks
Leo (training)	20	19	1 missed segment (due to edge effects)
Mac	6	7	1 redundant segment (due to edge effects)
Steamhouse 1	11	11	All segments comply to annotations
Steamhouse 2	15	15	All segments comply to annotations

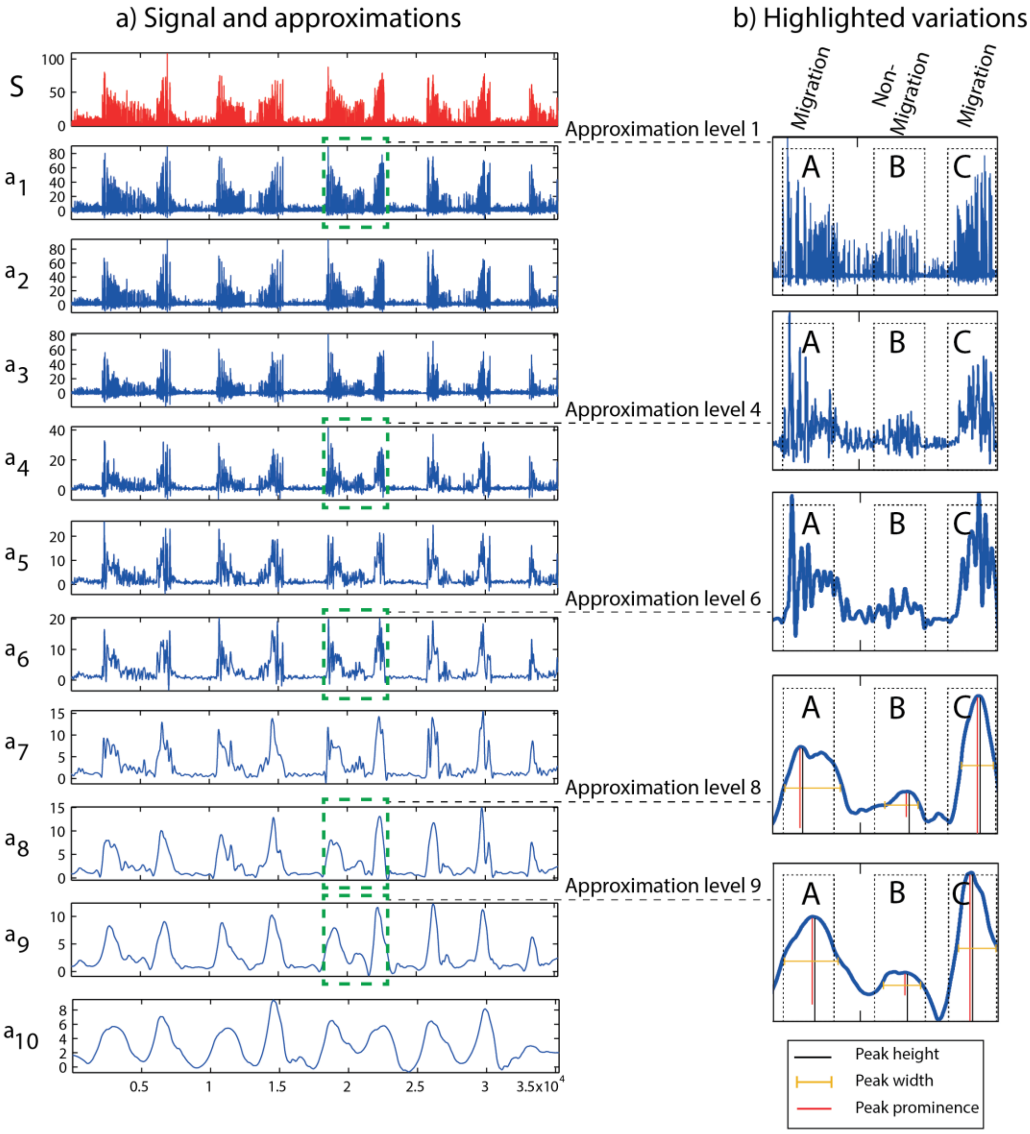

Figure 1. a) Speed profile and corresponding approximation sub-bands of a bird trajectory including migratory and non-migratory behaviors. b) Highlighted part of the signal at different DWT decomposition levels. Two phases correspond to same behavior: A and C denote migration, depicted by high values of speed. Phase B occurs during a non-migratory period. However, the speed values in Phase B are quite comparable to a large portion of both phases A and C and therefore B could be easily confused with the migratory seasons. The peak parameters including height, width and prominence are shown for the highlighted part of approximation level 9. The peak height is the value of the peak, whereas peak prominence is the distance to the higher local minima around the peak, before the peak intercepts a higher peak. Width is the horizontal line splitting the prominence in half.

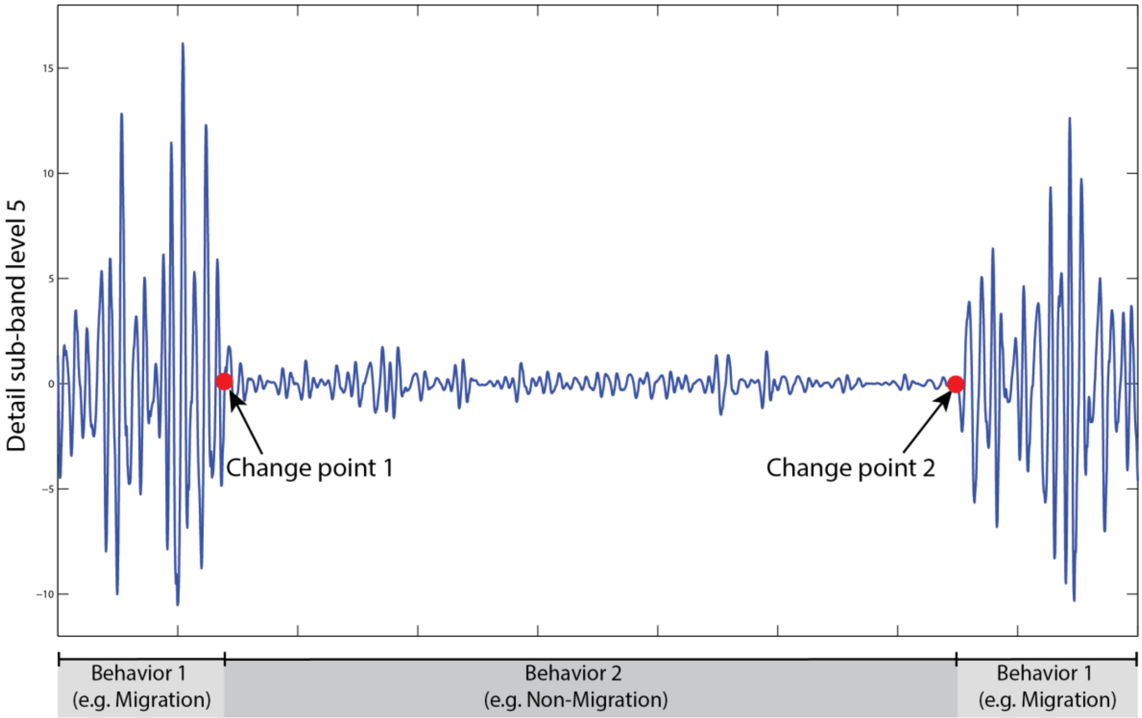

Figure 2. Abrupt frequency change in the detain sub-band caused by different behaviors. A change point is defined as a point where the difference to the previous point exceeds a certain threshold. By using annotated data, it is possible to relate the frequency content in the detail sub-bands to different behaviors.

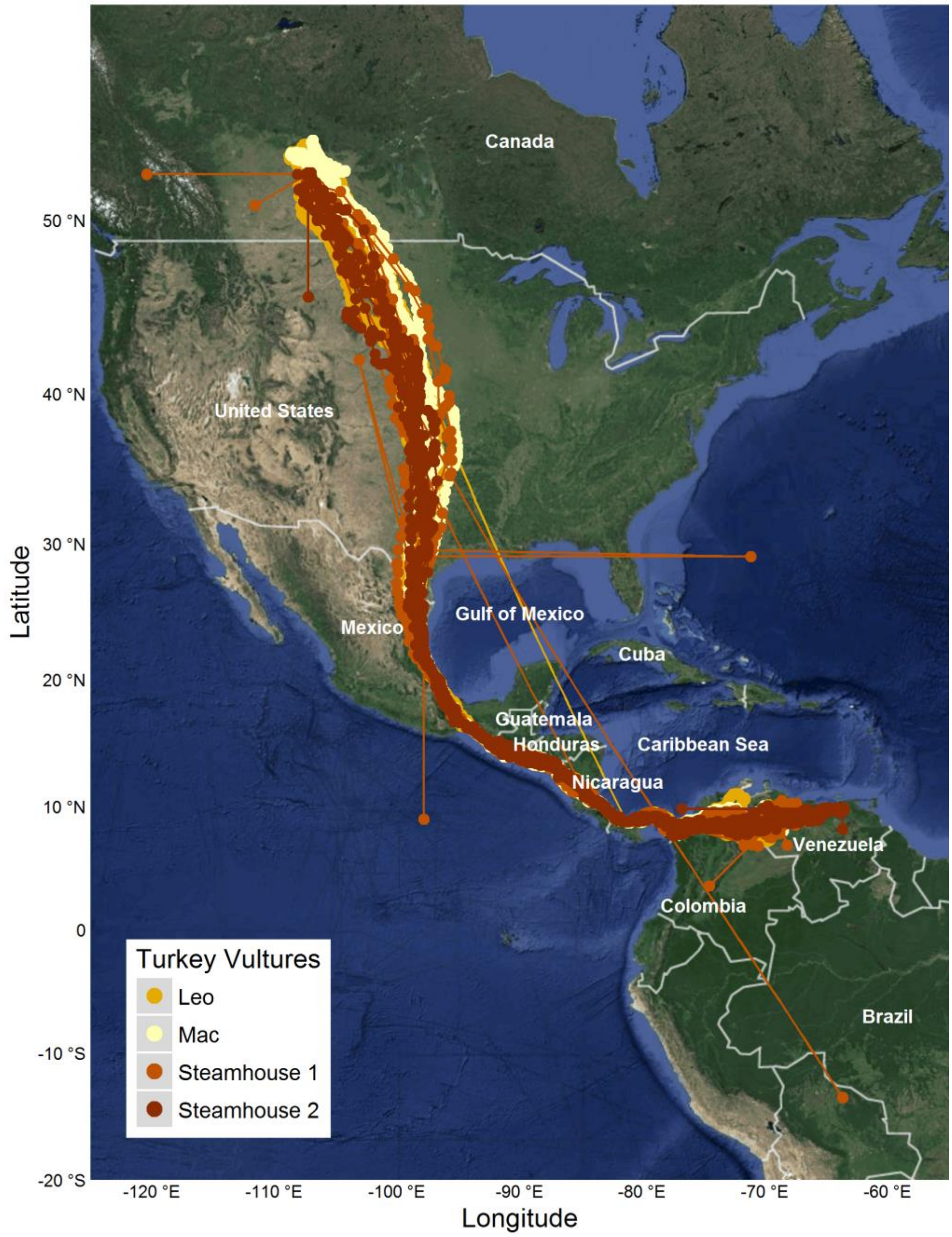

Figure 3. The trajectories of the four Turkey Vulture individuals studied. The migration starts from Canada to South America, pathing through central regions of the United States and Central America, and reverse. Some outliers (especially in the case of Steamhouse 1) are evident, however they were deliberately kept to assess the robustness of the proposed method.

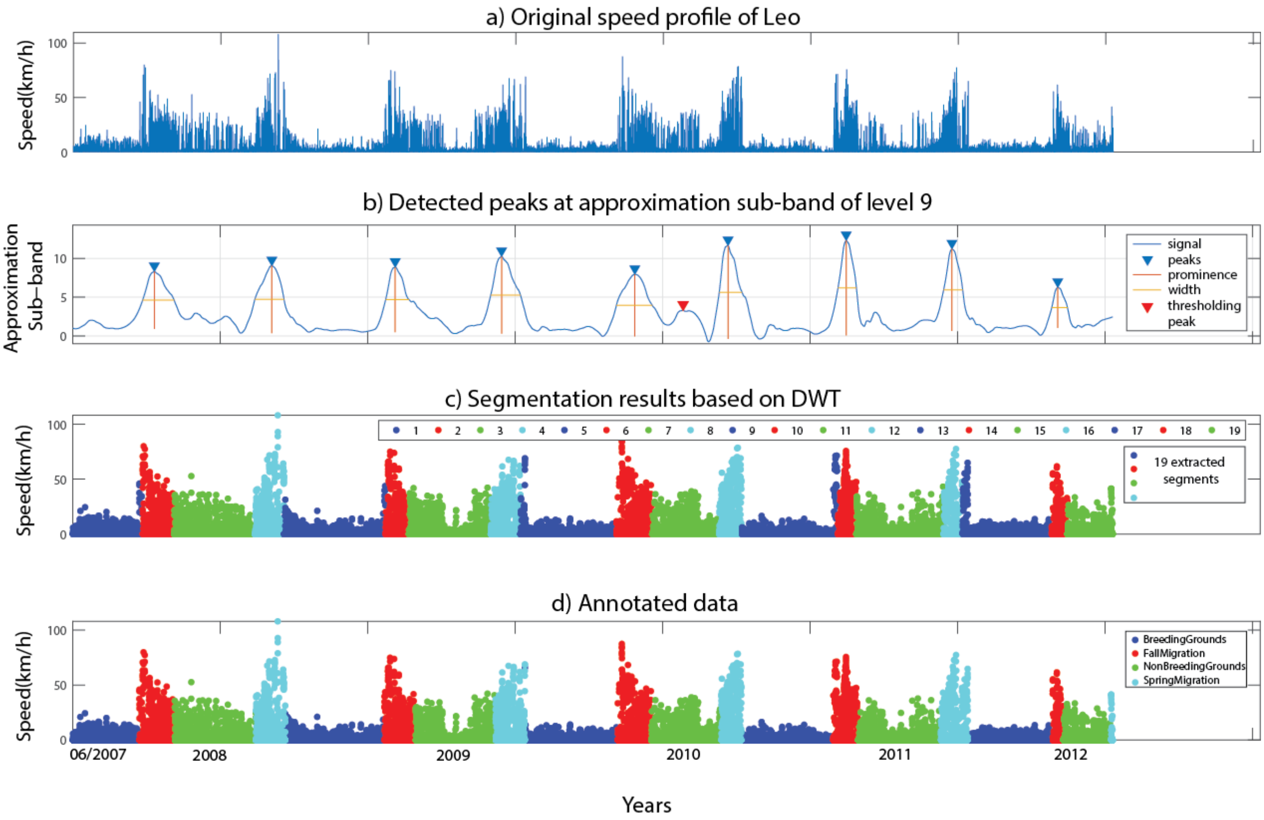

Figure 4. Applying the proposed segmentation method on data of Leo. a) Speed profile of Leo as the input signal for wavelet analysis. b) Detected peaks in approximation level 9 by thresholding the height of the peaks, in order to distinguish between migratory and non-migratory seasons. c) Segmentation results based on the width of the extracted peaks. The resulting 19 segments are closely representing the annotated data (shown in d).

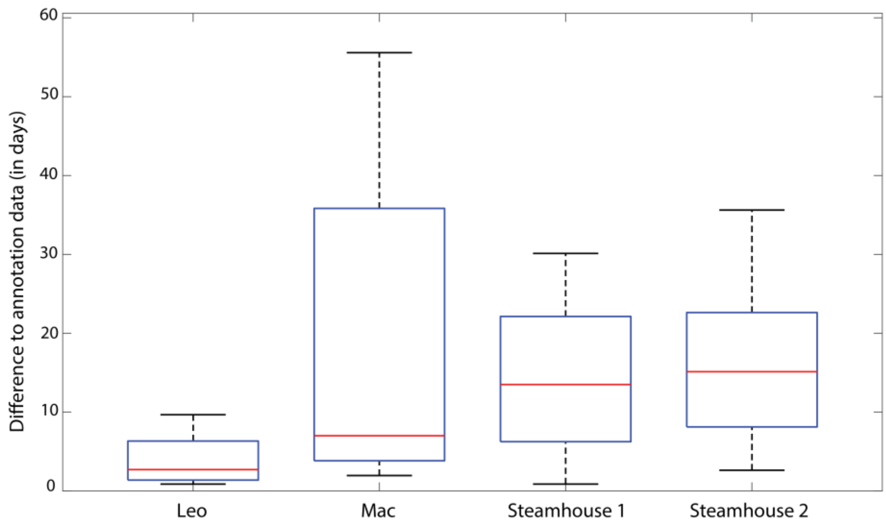

Figure 5. Temporal difference between extracted and annotated segments in the turkey vulture tracks.

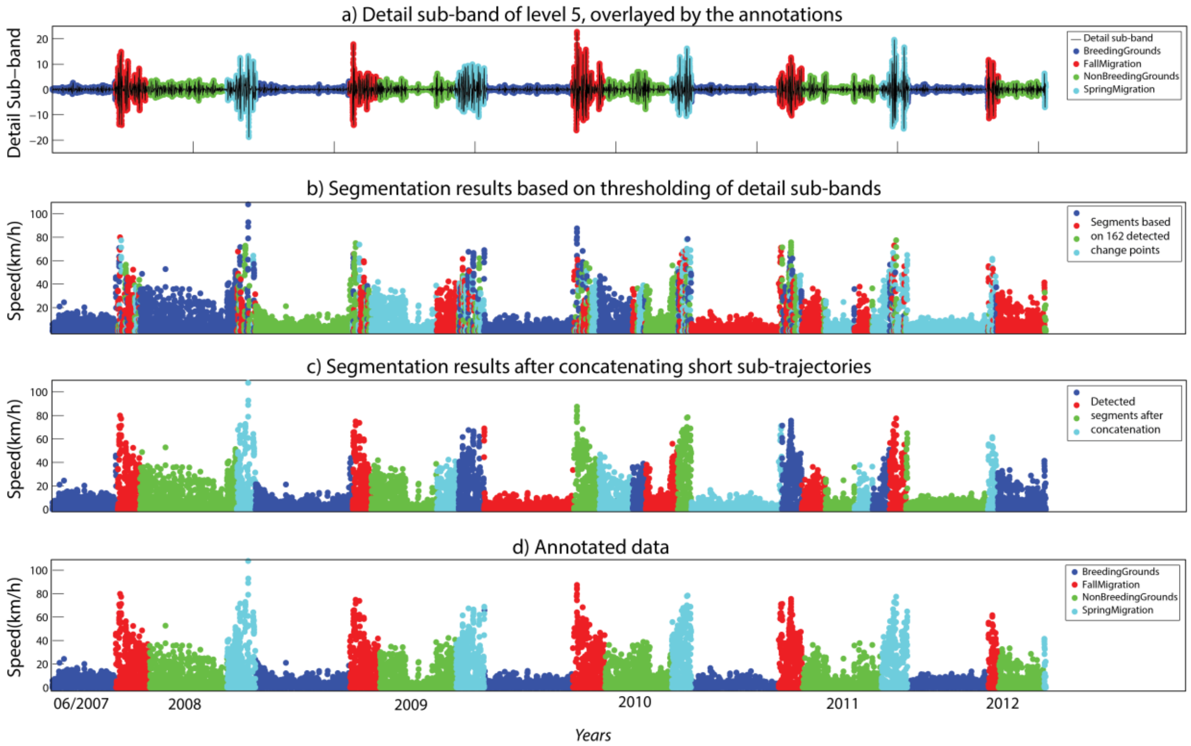

Figure 6. a) Overlaying the detail sub-band at level 5 over the annotation data. b) Detecting change points by thresholding the detail coefficients. High heterogeneity of detail coefficients results in numerous change points and therefore segments. This is particularly visible in the non-migratory seasons, where the variation in the high-frequency content of the signal is higher. c) After concatenating short sub-trajectories, segmentation results in 25 segments. This is an improved result compared to Figure 6b, but some redundant segments still remain.

Supplementary Information
(MEE paper)

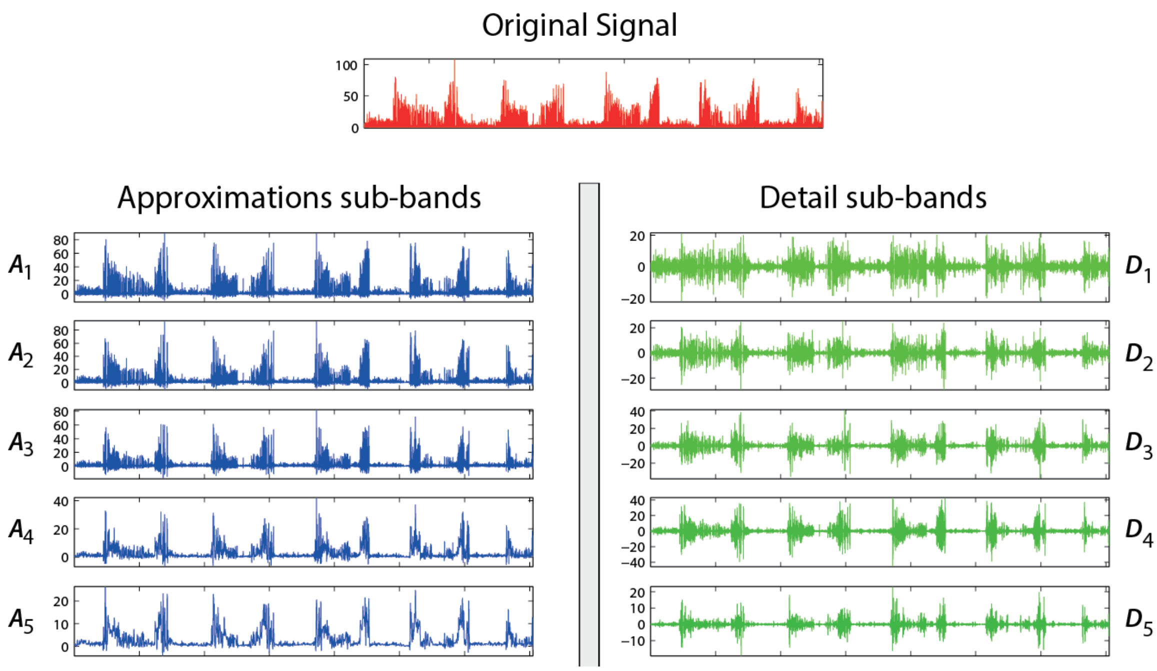

Figure S1. Example of decomposition of a signal using DWT. *The signal is passed through low-pass and high-pass filters to generate approximation and detail sub-bands. Aj represents the approximation sub-band at the jth level of decomposition using a low-pass filter and Dj represents the corresponding detail sub-band at the jth level obtained through the high-pass filter.*

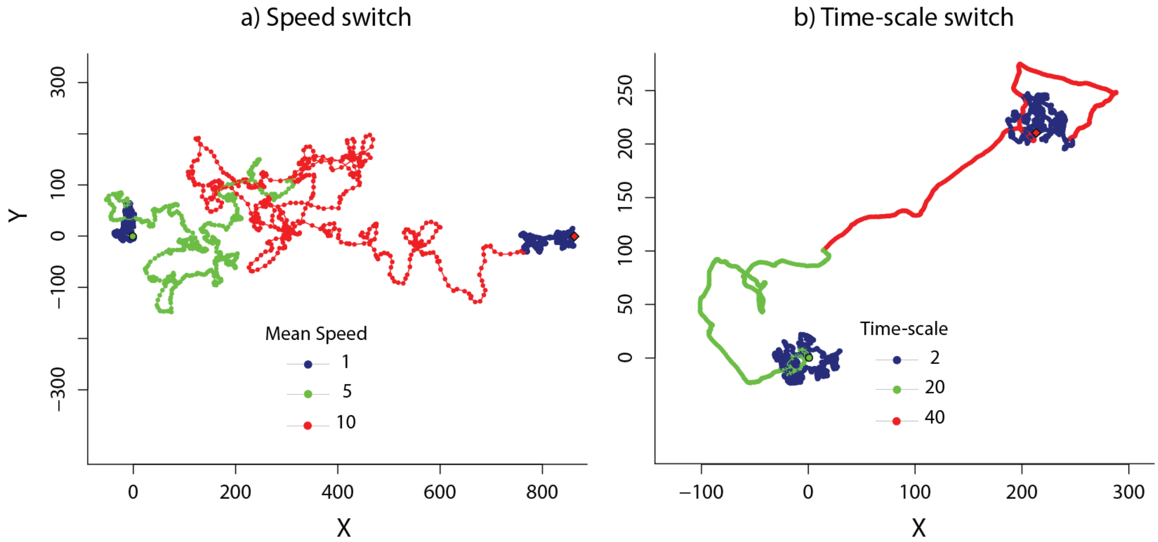

Figure S2. Examples of simulated tracks used for validation: *a) Speed switch model, where the values of mean speed are changing in different segments (1,5,10,1). b) Time-scale switch, where changing the time-scale (2,20,40,2) for the four modes results in segments of different tortuosity.*

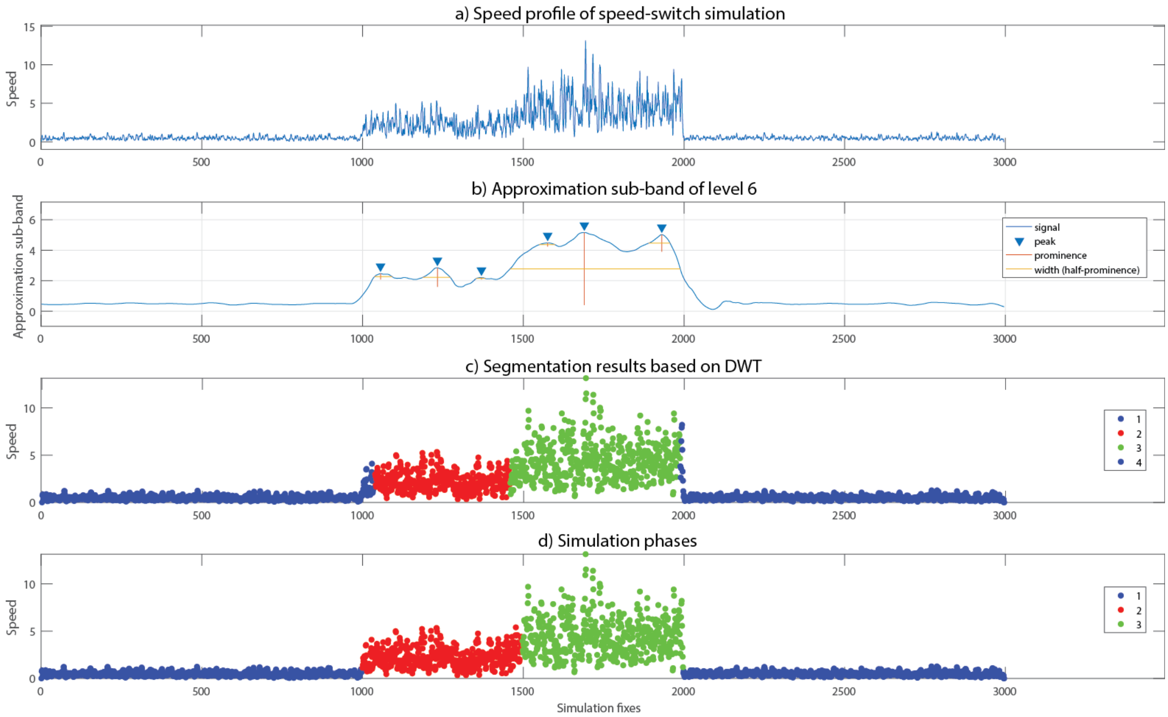

Figure S3. Applying the proposed segmentation method on the speed-switch simulation: *a) Speed profile of speed-switch model. b) Detected peaks in the approximation level 6 by thresholding the height of the peaks, in order distinguish between the three simulation phases. c) Segmentation results based on the width of the extracted peaks. The resulting 4 segments are closely representing the given simulation phases (shown in d).*

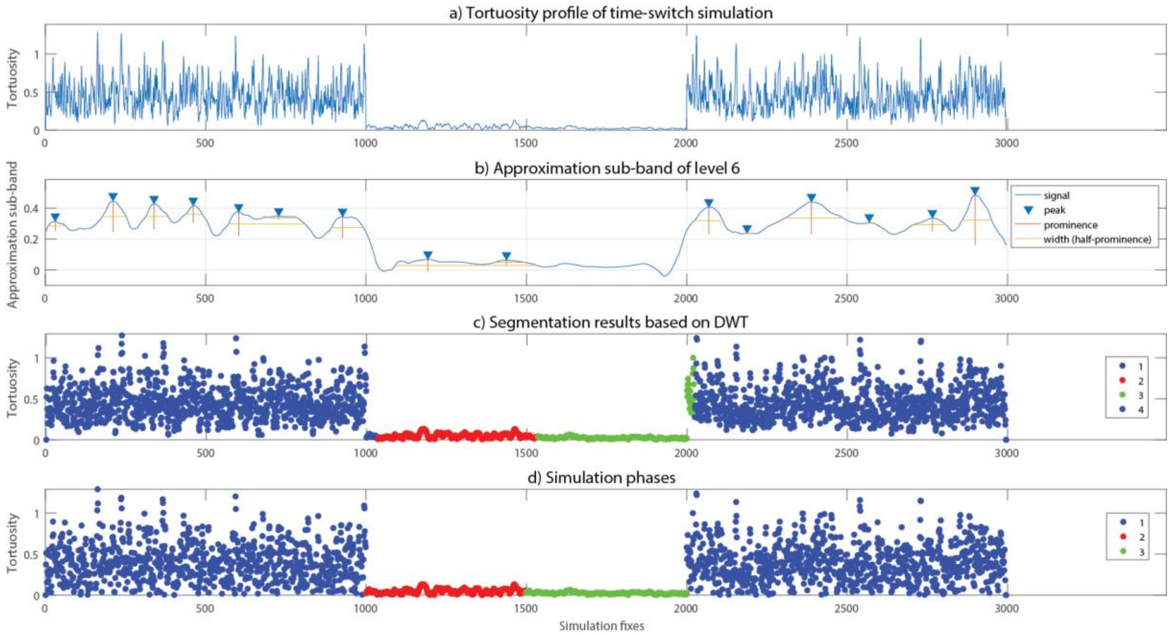

Figure S4. Applying the proposed segmentation method on the time-switch simulation: *a) Tortuosity profile of time-switch model. b) Detected peaks in the approximation level 6 by thresholding the height of the peaks, in order distinguish between the three simulation phases. c) Segmentation results based on the width of the extracted peaks. The resulting 4 segments are closely representing the given simulation phases (shown in d).*

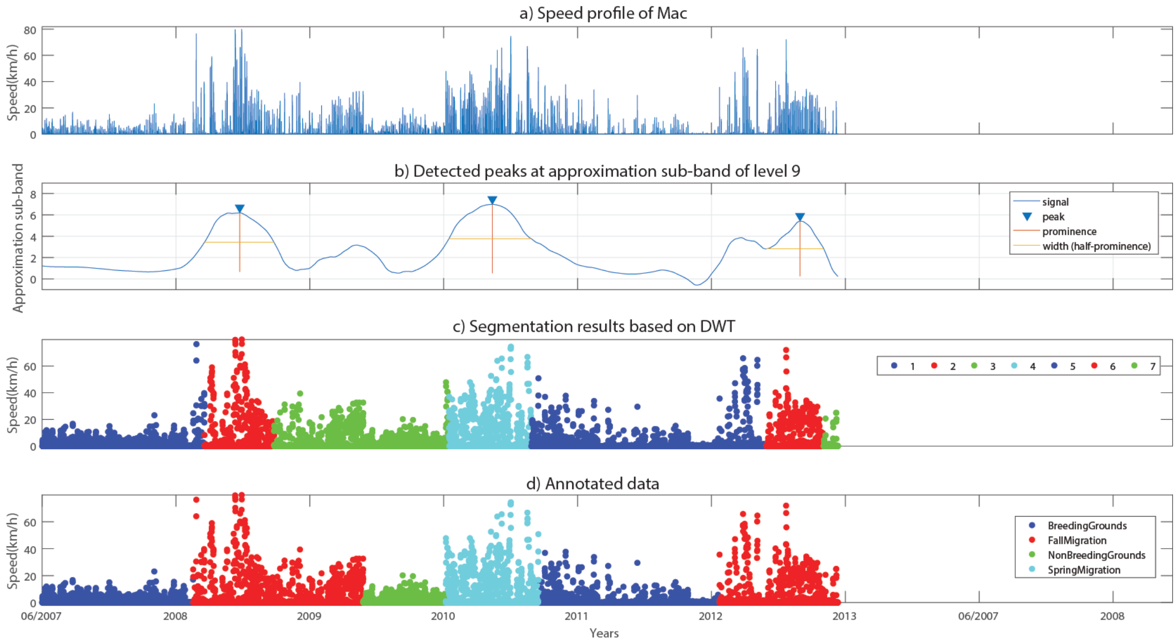

Figure S5. Applying the proposed segmentation method on data of Mac. *a) Speed profile of Mac as the input signal for wavelet analysis. b) Detected peaks in the approximation level 9 by thresholding the height of the peaks, in order distinguish between migratory and non-migratory seasons. c) Segmentation results based on the width of the extracted peaks. The migratory seasons in this individual has a very different behavior than Leo, therefore the difference between the resulting 7 segments to the annotated data (shown in d) is much higher. Note the redundant segment on the edge of the profile.*

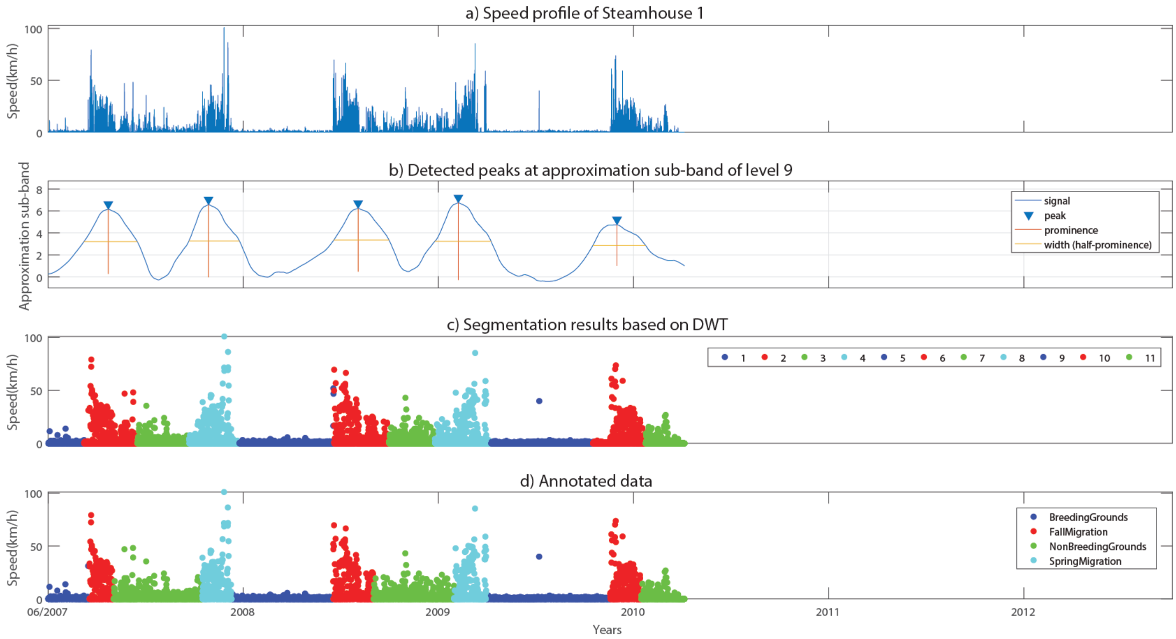

Figure S6. Applying the proposed segmentation method on data of Steamhouse 1. *a) Speed profile of Steamhouse 1 as the input signal for wavelet analysis. b) Detected peaks in the approximation level 9 by thresholding the height of the peaks, in order distinguish between migratory and non-migratory seasons. c) Segmentation results based on the width of the extracted peaks. The resulting 19 segments are closely representing the annotated data (shown in d).*

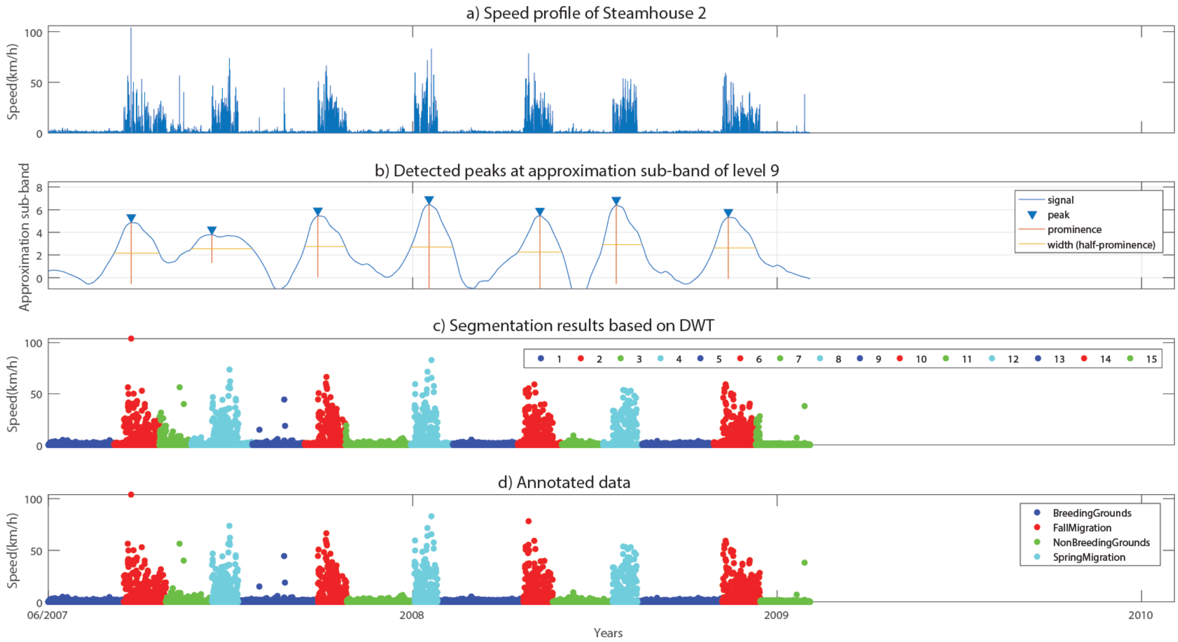

Figure S7. Applying the proposed segmentation method on data of Steamhouse 2. *a) Speed profile of Steamhouse 2 as the input signal for wavelet analysis. b) Detected peaks in the approximation level 9 by thresholding the height of the peaks, in order distinguish between migratory and non-migratory seasons. c) Segmentation results based on the width of the extracted peaks. The resulting 19 segments are closely representing the annotated data (shown in d).*

Chapter

6

Synthesis

6 Synthesis

With the large volumes of high-resolution movement data available nowadays, cross-scale analysis methods are needed for exploration of movement patterns across different scales. This thesis presented different methodological approaches for cross-scale analysis in the two highly relevant areas of movement analysis, namely movement classification and trajectory segmentation. This chapter brings the most pertinent outcome of this thesis together. To this end, the three main research questions are revisited and the results are discussed in Section 6.1. The interdisciplinary contributions of this research are discussed in Section 6.2. Section 6.3. draws general conclusions and the chapter ends with an outlook on potential future research directions in Section 6.4.

6.1 Main findings

- ***RQ 1: What are suitable methods to move from single-scale to cross-scale movement analysis?***

In this thesis, by focusing on the quantitative representation and classification of movement, scale was explored both in terms of 'spatial extent' and 'temporal resolution/granularity'. In the spatial domain, a partitioning scheme of the underlying movement space was used for exploring the spatial scaling. Similarly in the temporal domain, two methods — resampling and multilevel DWT decomposition — were used for temporal scaling. In the following, these cross-scale analysis methods in the spatial and temporal domains are discussed.

a. Spatial scaling through partitioning

In Chapter 2, subdividing the underlying spatial domain into different zones, and changing their size, was investigated for the behavioral analysis of Zebrafish movement data. The impact of aggregation and zoning in the analysis of spatial data has been already well-addressed through the Modifiable Areal Unit Problem (MAUP) (Openshaw 1984; Shortt 2009). The employed partitioning scheme invariably involves elements of the MAUP. However, the main difference to the common MAUP is that the selection of the zoning schemes in our case is biologically-driven. This is warranted by the need for evaluating the patterns mined at different spatial scales, as well as by partitioning schemes that are meaningful from the perspective of the behaviors of the moving object under study. In the case study of Chapter 2, a three-level partitioning scheme was used: macro-level (2-zones), meso-level (3-zones) and micro-level (9-zones). The results showed that drug treatments affect zebrafish movement behavior particularly in the corners, which could be captured only at the micro-level of spatial zoning (i.e. 9-zones). This supported the studying of Zebrafish movement at more finely-grained zones and acted as a novel insight for the domain experts in this particular case study, denoting the importance of spatial scaling in movement studies.

b. Temporal scaling through resampling

Simply calculating the movement parameters at one specific scale misses many important ‘micro-movement’ features that hold predictive value for behavioral research (Dodge et al. 2009). Hence, variation of movement parameters can be used to exploit relevant cross-scale behavioral patterns (Geyer et al. 1986; Paulus & Geyer 1991). In this thesis, a series of moving temporal windows (w_i) of different sizes were employed, within which the values of MPs were calculated (Laube & Purves 2011). As for the spatial scaling, the range of window sizes can be decided based on the temporal characteristics of particular behaviors in the movement study. The minimum temporal window size was selected as the original temporal granularity and the maximum was defined based on the approximate time needed for a full behavioral event to take place. For example, in the Zebrafish case study of Chapter 2, the temporal window sizes were varied in the 0.1 - 7.5 seconds range. However, in the case study of foraging birds presented in Chapter 3, this was decided to be 13 - 91 seconds. The results in both cases showed that the highest classification performance was always achieved in a temporal window that was larger than the original temporal window (i.e. the original sampling rate of the data). This might be because in a highly granular temporal window, there is not enough time for distinct behavioral events to unfold and therefore the signal might be discarded. By employing the temporal resampling method, an appropriate moving window is selected where behavioral patterns have enough time to be expressed. This is in line with the findings of recent studies (de Weerd et al. 2015), where the temporal resolution and length of the trajectory determined whether particular behaviors in trajectories of cows could be reliably detected or not.

c. Temporal scaling through multilevel decomposition methods

Other than the temporal resampling method, the DWT was employed as a more advanced method by providing a decomposition of MP profiles at different levels. In this thesis, the DWT was preferred over the continuous wavelet transform (CWT) for two main reasons: For classification purposes, the CWT will generate an excessive amount of data by calculating the coefficients at every possible scale, which cannot easily be aggregated and fed into the classification model. Similarly for segmentation purposes, it is very hard to interpret the map of coefficients provided by the CWT and link them to the movement patterns. In contrast, the DWT chooses only a subset of scales and sampling positions and is just as accurate as the CWT (Mallat 1999; Khorrami & Moavenian 2010). In this thesis, the full content of the DWT including the approximation and detail sub-bands was employed simultaneously, which had not been used in the previous movement studies.

In Chapter 4, the DWT coefficients were used in the classification of ciliate species. Extracting those features not only improved classification performance, but may also point out new behaviors in movement. In Chapter 5, a segmentation method based on the DWT was proposed to detect behavioral phases in real and simulated data. By taking the cross-scale effects into account, the segmentation approach based on the DWT can be considered as a novel approach for detecting behavioral segments in movement data.

- ***RQ 2: Which movement features contribute to multi-scale classification of movement? And to what degree?***

Based on the above cross-scale analysis approaches, a methodology was proposed in Chapter 2, where movement features measured across different spatial and temporal scales are extracted in order to obtain a joint model of behavioral classification. The methodology consists of three main stages: extraction of features first in the spatial and second in the temporal domain, followed by the integration of such features for the final classification model in the third stage.

a. Features related to spatial scaling

In the case study of Chapter 2 and based on the hierarchical partitioning scheme, the time spent in different spatial zones was computed. Since the drug treatments cause different behaviors, the 9-level partitioning scheme provided additional features to the classic neurobehavioral studies (Kafkafi & Elmer 2005; Cachat et al. 2011). The fish are moving mostly in the top of the tank when treated with anxiolytic drugs, whereas anxiogenic drugs increase anxiety and cause the fish to stay along the bottom. Computing the time spent in the fine-grained zones (i.e. edges and corners) allow to discriminate between those treatments.

In Chapter 3, the importance of underlying space was evaluated by introducing geographic location (i.e. latitude) as input feature in the classification model. Using this feature, the effects of the geographic context was evaluated on the foraging behavior of Oystercatcher. They feed on shellfish and ragworm on the mudflats (south of latitude 53.47º). Conversely, on the saltmarsh and meadows (between 53.47º and 53.48º) they eat earthworms and insect larvae. The differences in habitat structure and prey types are reflected in different movement patterns.

Similarly other spatial features may be extracted, including characteristics of movement parameters within different zones, contextual information linked to the zones, or the frequency of transitions between zones. In both of the case studies reported in Chapters 2 and 3, respectively, the features related to the spatial domain played a prominent role in the classification. This was observed by running classification experiments solely based on spatial features and evaluating their importance based on the achieved classification performance. Following that, the scale range at which the highest classification performance was achieved was selected as the reliable spatial scale of analysis.

b. Aggregate movement features related to temporal scaling

The features related to the temporal domain extracted in the second stage of the proposed classification methodology investigate the variation of movement patterns engrained in the trajectory of a moving object across different temporal scales. The MPs used throughout this thesis include speed, acceleration, turning angle, meandering, and sinuosity. In the case studies reported in Chapters 2-4, statistical descriptors of MPs (e.g., the global minimum, maximum, mean and standard deviation) were computed over the entire trajectory, as input features for the classification model. In Chapter 2, it was the first time that collection of those features were employed for studying Zebrafish behavior. For example, by using meandering features it was possible to capture the effects of erratic movements caused by anxiogenic treatments. Similarly in Chapter 3, although sinuosity had been already used in flying birds (Grémillet et al. 2004; Weimerskirch et al. 2002), it was the first time to use the combination of sinuosity and MSSI for classifying foraging behaviors of wading birds. In Chapter 4, using models based on movement features yielded comparable results to standard morphological models in other studies (Joo et al. 2013; Bell & Hopcroft 2008; Amer et al. 2011; Relyea 2001). Moreover, approximate entropy (ApEn) was used as a further example of aggregate movement features (Li 2014), allowing us to quantify fluctuations in particular ciliate species. Similarly in the spatial domain, the performance of the classifier was evaluated based on features computed at different temporal windows, yielding the reliable scale of analysis in the temporal domain.

c. DWT coefficients

The multilevel decomposition of MP profiles in the DWT can provide further cross-scale features for movement classification. By transforming the MP profiles into the frequency domain, the DWT can detect additional patterns that go undetected if only simple movement features are employed. Examples include temporal autocorrelation (Dray et al. 2010), periodicity patterns (Riotte-Lambert et al. 2013) and change point detection (Sur et al. 2014). In other applications such as the classification of EEG signals, wavelet analysis has been successfully applied, owing precisely to the periodic nature of the signals (Güler & Ubeyli 2005; Subasi 2007). Contrary to those classification studies, however, where only a selected subset of wavelet coefficients was used, in this thesis the full set of approximation and detail sub-bands were exploited. This is due to the fact that in movement classification, the behavioral patterns that form the movement classes manifest themselves at intervals that cover a certain time period and thus affect the general structure of the signal. Therefore, both the approximation component (indicating the general structure) and the detail components (indicating abrupt changes) were used.

The results of Chapter 4 demonstrate three advantages of DWT features. First, they drew out some ciliate species that always went undetected using general movement features. This is due to a looping behavior where individuals move away from their departure point and return within a given time period. It is most likely that these movements are performed on a small spatial scale such that they were captured by the wavelet analysis. Although movement is not necessarily a periodic process by nature, the case study of ciliate species identification showed that the DWT is able to detect periodic elements in the non-stationary movement time series. This is highly relevant for the study of movement, since periodicity occurs only irregularly through the data.

Second, this study shows that wavelet analysis provides complementary information to static movement parameters and hence improves classification success by capturing an additional aspect of movement. Explaining such behaviors was a highly interesting result for the domain experts, since they could not be explained by the standard biological models (Relyea 2001; Jordan et al. 2013; Pennekamp et al. 2015).

The third advantage of employing DWT refers back to its ability in detecting the abrupt variations in the movement signals through the high-frequency content of DWT sub-bands, a property that was exploited in more detail in the use of the DWT in segmentation problems (see next section).

From a methodological point of view, the baseline methodology introduced in Chapter 2 is further extended by wavelet-based feature extraction to support the classification of recurring and cyclical behaviors. The summary of the three classification tasks are shown in Table 6.1. Improvement of the classification performance shows that cross-scale analysis bears great promises in matching the scale of analysis to the scale of phenomena under study. In cases of Zebrafish and Oystercatcher movement data, the obtained classification performances based on features computed at different spatial and temporal scales was used to accurately define the analysis scale. The 9-zones subdivision and temporal window of 5 seconds chosen in Zebrafish case study were biologically relevant scales for the zebrafish behavioral states to play out. Similarly in the Oystercatcher case study, window size of 1 min showed a relevant analysis scale to investigate foraging behaviors in those wading birds. Those results wouldn't have been possible if the data was analyzed only in one specific scale.

In case of ciliates movement data, the same resampling method for computation of MPs resulted the highest classification performance for the original temporal granularity. This can indicate that even higher resolution data or longer trajectories are needed to use the proposed resampling approach. However, adding features based on the DWT, as another multi-scale measure, contributed to improving the performance of the classification and helped to identify more species. Similarly in case of Oystercatchers, MSSI showed to be a predictive variable by giving more details about the foraging behavior that the general MPs could not. From this, it can be concluded that scale issues are manifested in different ways and therefore appropriate methods need to be used in order to provide complementary measures to scale-specific techniques.

In terms of classification methods employed, it was found out that careful selection of input features to obtain a set of features that collectively capture the varied aspects of movement will result in the highest classification performance, regardless of the classification method used. This was observed specially in ciliates case study, where the two classification methods with different theoretical background (i.e. SVM and DT) resulted in the same performance. Therefore, employing cross-scale analysis methods is of utmost importance for selecting relevant movement features. Such a classification approach has a clear potential to ensure reliable results and should be investigated further for other applications of behavioral classification of movement.

Table 6.1. Summary of the three classification tasks and remarks on the employed cross-scale analysis in the feature extraction and classification of movement

Case study	**Task**	**Features sets**		**Classification methods / results**	**Remarks on classification performance**
		Spatial	**Temporal**		
Zebrafish	Classifying three Anxiogenic, Anxiolytic and Controlled drug treatments	✓ Time spent in the 2, 3 and 9-zones sub-divisions of space	✓ Statistical descriptors of MPs at window sizes of [0.1—7.5 sec]	SVM for classification, Genetic algorithm for feature selections, Accuracy: 92%	9-zones partitioning in the spatial scale and window size of 5 seconds for temporal scale achieved highest accuracies.
Oystercatcher	Classifying foraging vs. non-foraging behaviors	✓ Geographic location (i.e. latitude and longitude)	✓ Statistical descriptors of MPs at window sizes of [13— 91 sec] + MSSI	Decision tress for classification Accuracy: 78%	Latitude acts as a predictive feature. Sinuosity of window size of 1 min and MSSI of size 24, 8 and 4 achieve highest classification accuracies
Ciliates	Classifying eights ciliate species: Paramecium caudatum, Paramecium aurelia, Blepharisma japonicum, Colpidium striatum, Colpidium campylum, Cyclidium glaucoma, Tetrahymena thermophila and Loxocephalus sp	× Morphological features were used instead	✓ Statistical descriptors of MPs + DWT coefficients + ApEn	SVM and DT for classification, Genetic algorithm for feature selection Accuracy: 95%	Morphology acts as the baseline. Gradually adding movement features improves the performance. Specially DWT detect some species which other features cannot.

- ***RQ 3: How can multilevel decomposition methods contribute to segmentation of trajectories in presence of abrupt and continuous changes in movement?***

The proposed segmentation method based on the DWT was used in Chapter 5 for extraction of behavioral segments. The method was first applied on the simulated trajectories and then it was used to detect migratory patterns in real movement trajectories of turkey vultures.

By choosing a relevant MP signal, all four behavioral segments in the simulations were precisely detected. According to Gurarie et al. (2015), the state of the art segmentation methods suffer from two major drawbacks. The first one relates to model misspecification: the dependency of the method on a specific movement parameter may ignore the effects of other influencing variables. The second problem relates to the fact that the existing techniques often do not support a systematic way for considering the autocorrelation effects and therefore fail to determine the magnitude of changes in the extracted movement modes.

The use of approximation sub-bands at different decomposition levels allows for to taking the autocorrelation effects into account and investigate the continuous variations in the data. This is in accordance with the findings of other studies, where the changes in movement might not be abrupt but continuous (Gaucherel 2011; Patroumpas et al. 2015). Moreover, the possibility of choosing the relevant response variables resulted in precise segmentation in both of the simulations. The DWT, on its own, is not dependent on any specific movement parameter. Therefore, depending on the desired behaviors, different MPs can be employed to investigate their influences. This addresses the model misspecification problem, since the method is not dependent on any particular movement parameter, instead multiple responses may be tested. For detecting the magnitude of changes, the employed peak analysis serves as an efficient way of estimating the length of the extracted segments. Compared to the three methods first passage time (FPT), behavioral partitioning of movement models (BPMM) and behavioral change point analysis (BCPA) presented in Gurarie et al. (2015), the results based on the proposed segmentation method were better by accurately determining the number of segments, as well as how well the segments match to both simulations.

The results on the Turkey Vulture dataset showed that the approximation sub-bands in combination with the peak analysis was able to retrieve the annotated segments in all the trajectories. Using detail sub-bands afterwards to detect fine-scale behaviors resulted in detecting numerous change points, which has the potential to identify behavioral states within the migratory/non-migratory phases and mine movement trajectories for cryptic behaviors.

Table 6.2. Summary of the findings of applying DWT in segmentation of simulated and real trajectories

<table>
<tr><th>Trajectory</th><th>Type</th><th>True N. of segments</th><th>N. of extracted segments</th><th>Average difference</th><th>Remarks</th></tr>
<tr><td>Speed-switch</td><td rowspan="2">Simulation</td><td>4</td><td>4</td><td>30 (fixes)</td><td rowspan="2">The method outperforms the state-of-the-art methods by correctly identifying the segments in both simulations</td></tr>
<tr><td>Tortuosity-switch</td><td>4</td><td>4</td><td>32 (fixes)</td></tr>
<tr><td>Leo</td><td rowspan="4">Turkey vulture</td><td>20</td><td>19</td><td>4 (days)</td><td rowspan="4">The method detect almost all of the segments correctly, unless for the very short segments on the edges of the track.</td></tr>
<tr><td>Mac</td><td>6</td><td>7</td><td>20 (days)</td></tr>
<tr><td>Steamhouse 1</td><td>11</td><td>11</td><td>14 (days)</td></tr>
<tr><td>Steamhouse 2</td><td>15</td><td>15</td><td>15 (days)</td></tr>
</table>

To summarize, while the detail sub-bands were most appropriate to detect dominant change points in the profiles of movement parameters, the strength of approximation sub-bands was in localizing the variations in the movement signal to capture the continuous transitions between the behavioral modes. By employing relevant movement variables, the DWT related the representation signals (i.e. DWT sub-bands) to multiple behavioral phases in both the real-world and simulated datasets. The summary of the results of applying DWT for trajectory segmentation is shown in Table 6.2. Comparing the number of extracted segments to the actual number of segments an also the difference between those segments showed that DWT performed better compared to the state-of-the-art methods.

6.2 Interdisciplinary nature of research

Movement research is a multi-disciplinary field and the developed methods are much more valuable once they benefit from mutual engagement and collaboration between the developers of the analysis methods and the domain experts (Demšar et al. 2015). Therefore, in order to be applicable to a variety of research fields involved in the study of movement (ecology, environmental sciences, cognitive sciences, transportation, etc.), such analysis methods should comply with the research needs in those domains. Based on these facts, four particular sub-projects were conducted in this PhD project, in collaboration with domain experts from different areas of research. This not only helped fulfilling the research needs and therefore contributing to those areas, but a methodological storyline was also built, advocating cross-scale analysis to address scaling issues in movement research. Such engagement with experts from different areas allowed to demonstrate that cross-scale analysis was relevant in all of those studies.

In the study reported in Chapter 2, the proposed cross-scale methodology was employed on video tracking data of adult zebrafish, in collaboration with a neuropharmacology group at Tulane University, USA. The obtained classification model, as the main outcome of this collaboration, was a new product for the domain experts to automatically classify trajectories. Therefore, reaching a classification accuracy of ~92 % was judged by the experts to be a valuable contribution in neuropharmacology studies. This collaboration also helped to fine-tune the parameters of the employed cross-scale analysis approaches, for example to decide on the length of the temporal windows used.

The work of Chapter 3 was a collaboration with animal ecologists at the University of Amsterdam. While foraging behavior is typically detected by the use of accelerometer sensors, the outputs of this study showed that careful design of movement features can reach a sufficient classification accuracy (i.e. 78%). While most of the works based on trajectory features of such birds were rather descriptive (Weimerskirch et al. 2002; Grémillet et al. 2004), the outcome of this study can be used for building predictions models in cases where no additional sensor or observational data on behavior is available.

The application problem reported in Chapter 4 was classifying ciliate species in collaboration with biologists at UZH. The collaboration with the experts allowed to investigate movement features as a complementary proxy to morphology when classifying ciliate species. Moreover, the scalability of such analysis on datasets that comprise many more than the 10 – 100 individuals in standard experimental designs (e.g. Boyce et al. 2010; Sur et al. 2014) were evaluated by using data from almost 4000 trajectories. Adding movement features significantly improved the classification performance to almost 95%.

In Chapter 5, engagement with the experts was helpful in order to parameterize the proposed DWT method in a biologically-driven way. The method addressed some of the fundamental shortcomings of existing methods in the literature and can be considered as an important step forward to characterize different forms of change in movement data.

Moreover, some of the developed methods made use of well-established methods from other areas and adapted them in order to solve research problems in movement study. The DWT has its roots in signal processing and there are dozens of publications on its usage in various areas. However, no example of using the approximation sub-bands for behavioral characterization could be found. Therefore, this may be considered as a contribution to those areas too. In conclusion, this PhD thesis can be considered as an interdisciplinary research project, where techniques from other areas were adapted, thus providing innovative approaches and methods to extend the existing GIScience tool set for the classification of movement data. The outcomes shall contribute to a better modeling, understanding, and ultimately behavioral prediction of the moving objects under study, in order to unveil insights about the behavior of such objects in a variety of disciplines.

6.3 General conclusions

6.3.1 Summary

This thesis was motivated by the desire to develop a holistic view for cross-scale analysis of movement data. Figure 6.1 summarizes the elements of this work.

Cross-scale analysis was employed in two analysis tasks, i.e. movement classification and trajectory segmentation. The two types of cross-scale analysis methods are shown in the Figure 6.1: resampling of MPs at different temporal and/or spatial scales (Chapters 2 and 3) for providing classification features; and frequency-based techniques, in particular discrete wavelet transform, where the profiles of MPs are treated as the input movement signals in classification and segmentation problems (Chapters 4 and 5).

In the movement classification task, cross-scale analysis was introduced in the feature extraction step. In Chapter 2, a comprehensive methodology was introduced for integrating cross-scale features in the spatial and temporal domains for movement classification. The methodology was further used in Chapter 3 to assess the capability of cross-scale features in the classification of fine-grained behavioral modes. In the two classification experiments of Chapter 2 and 3, the correct analysis scale was identified through the proposed cross-scale analysis approaches. Feature extraction in the frequency domain was introduced in Chapter 4, as an addition to the baseline classification methodology to extract more advanced features using the DWT coefficients. By improving the classification performance, cross-scale analysis outperformed single fixed-scale analysis in all of the addressed classification tasks.

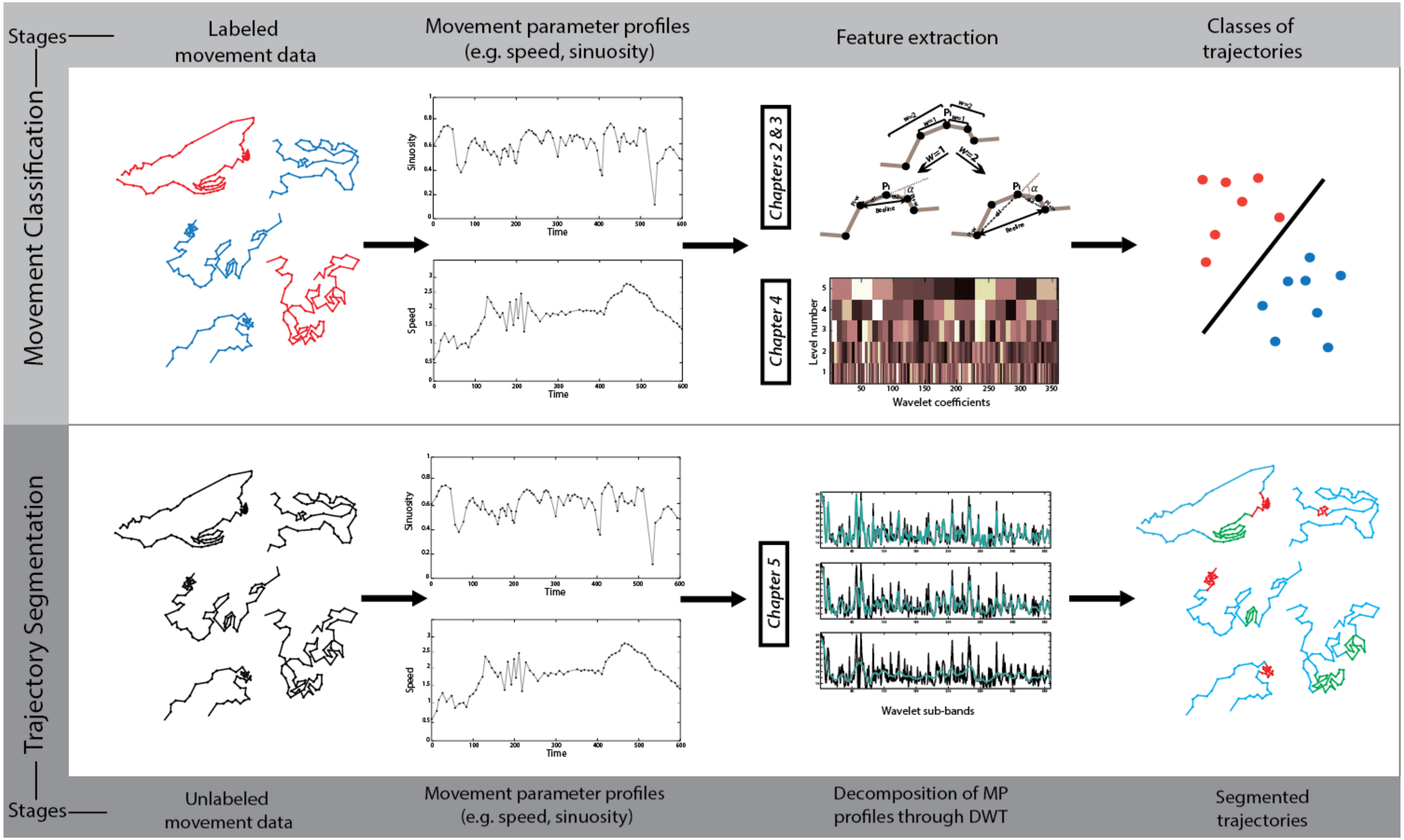

Figure 6.1. An overview of the addressed movement analysis problems. The contribution of the cross-scale analysis approaches introduced in this thesis are highlighted in the feature extraction for movement classification and segment detection in trajectory segmentation . The stages involved in movement classification are shown in the upper plot. After generating MP profiles from the labelled movement data, distinguishing features have to on extracted for classification. The contribution of this thesis in movement classification lies in this stage, where cross-scale analysis methods (including resampling and DWT coefficients) were used to generate movement features (Chapters 2, 3, 4). The lower plot indicates the stages involved in trajectory segmentation. The cross-scale analysis approach based on DWT decomposition was employed in this thesis to identify behavioral patterns across different scales (Chapter 5).

In the addressed movement classification problems, cross-scale analysis treated different number of classes (two, three and eight in chapters 2 to 4 respectively), as well as different number of trajectories. Moreover, he classes were related to different levels of trajectories, i.e. conceptual classes (drug treatments in case of zebrafish or species in case of ciliates) over the entire trajectory or behavioral classes at the level of sub-trajectories (foraging in case of oystercatcher). These demonstrate that the methodology is sufficiently generic to be adapted to different contexts of usage and also scalable to different types and amounts of data.

The importance of cross-scale analysis was further investigated in trajectory segmentation in Chapter 5. By sing the hierarchy of analysis levels provided by the DWT, cross-scale analysis performed better or equally well to the standard techniques used in the literature for trajectory segmentation. The proposed segmentation method based on DWT improves the quality of behavioral characterization of movement data by simultaneously characterizing both change points and continuous transitions in movement.

This thesis also highlighted the interdisciplinarity of movement by firstly employing methods from different areas including machine learning and signal processing and secondly having practical applications in a variety of application domains, including neuropharmacology, movement ecology and environmental sciences.

6.3.2 Overview of main contributions

The main contributions are to be found in the feature extraction step in movement classification, as well as the use of multi-level decomposition in trajectory segmentation.

The development of cross-scale analysis in those operations is both novel and timely. The importance of cross-scale movement analysis was first emphasized by Laube & Purves (2011). In this thesis, their proposed resampling approach was employed for providing features in movement classification. Moreover, the scaling of the spatial domain was also investigated as an addition to their work. Importantly in all the case studies, the domain knowledge was used to inform the process of defining the extent of scaling and therefore the obtained analysis scales is validated by the knowledge of the domain experts. Also more advanced features, such as DWT coefficients were employed in the classification. Typically the state-of-the-art methods treat movement only in the spatial or temporal domain, which is inevitable as these two dimension act as the underlying dimensions of movement process. However, one should consider the potentials of frequency-based methods in movement analysis. The DWT was employed as a more flexible approach than the standard frequency-based techniques, by not only looking at the time and frequency variations, but also due to its localization capacity in varying the resolution (i.e. scale) of analysis (Fagan et al. 2013). For example in the classification problem addressed in Chapter 4, the periodicity patterns detected through DWT would have been overlooked (or at least would have been hardly detectable) by using classic movement analysis methods in the spatial or temporal domain. Therefore, this thesis can be considered as the first attempt for exploring cross-scale analysis in movement classification and how those method help in better explaining the movement classes. Those techniques, eventually, offer the flexibility of determining the proper analysis scale in relation to the behavioral movement patterns expressed at different scales.

Similarly in trajectory segmentation, a hierarchy of analysis levels were introduced by the use of the DWT, giving further insights about the variations of movement patterns in MP profiles. So far, there was no method that can simultaneously characterize both change points and continuous transitions in movement. From a methodological point of view, this was a novel contribution for the usage of DWT decomposition in trajectory segmentation. However in the current literature, the approximation sub-band only at the final decomposition level has been used (Güler & Ubeyli 2005; Subasi 2007; Khorrami & Moavenian 2010) and mainly in classification tasks. The results of Chapter 5 demonstrate the great potential of using all the approximation sub-bands of DWT for characterizing the changes in movement patterns across different scales. The details sub-bands were also used for detection of change points and more fine-scale behaviors. Therefore depending on what level of changes are to be investigated, both of these components were used interchangeably.

The proposed methods in this work, however, are not without downsides. In the classification, more features are needed to be extracted to investigate even further aspects of movement. Particularly is the spatial domain, the use of simple features highly contributed to the classification performance and therefore more advanced features in this domain need to be explored. Also, features related to the contextual factors should to be integrated in the classification, in order to investigate the effects of external factors on movement. In the temporal domain, it was sometimes difficult to define a reasonable of range of window sizes for computation of MPs. Although this was always discussed with the domain experts, more automated approaches may be employed to drive such processes. In case of segmentation, the boundary effects in the DWT seems to be a challenging issue, resulting in lower-quality results on the edges of the track. This is a known down-side of wavelets, termed as “cone of influence” (Cazelles et al. 2008). Therefore, it is recommended that segments or parts of segments affected this are discarded or at least interpret with great care. Another downside may be that wavelet analysis is also quite demanding in terms of sampling frequency and length of the movement profile, however, the ever increasing performance of modern GPS transmitters is likely to solve that issue soon.

6.4 Future directions and outlook

Considering the fact that most of the behavioral changes are due to changes in the surrounding environment (or as some authors call it, context), there are very few examples in the literature of context-aware movement analysis (Gschwend 2015), let alone context-aware cross-scale movement analysis. Therefore, as a potential direction for future studies, the use of the proposed cross-scale analysis approaches should be considered in relation to the embedding context.

As the second direction, employing knowledge-driven methods may be considered for the classification and segmentation problems. Considering the dependency between behavioral changes in movement, this knowledge can be considered in the classification or segmentation methods. In the following, these two potential research strands as the extension of the proposed methods of this thesis are explained in more detail.

6.4.1 Context-aware movement analysis

The proposed segmentation algorithm based on the DWT may be further extended for characterizing behaviors in response to environmental change. The input signal for wavelet analysis, for instance, may be considered as the distance of moving objects to specific landmarks in the surrounding environment. As an inherently cross-scale analysis approach, decomposing the input signal into different levels through wavelet analysis can give us insights about changes in the behavior of objects at different analysis scales. Therefore, the effects of landscape disturbance on the movement can be measured according to future changes in the environment. Predicting movement in a heterogeneous environment requires assessment of movement patterns across different scales and wavelet analysis can potentially be employed to detect such cross-scale responses.

6.4.2 Dependency-aware movement classification and segmentation

An important note regarding movement classification and trajectory segmentation is considering the fact that changes in the movement characteristics are continuous along the trajectory. For example in classifying bird trajectories into flying, locomotion, foraging and other modes, the dependencies between the consecutive fixes and behavioral modes should be considered in the classification output. Meaning that it might not be possible (or highly unlikely) to immediately switch from a certain behavior to another one in the following fix of the trajectory. Therefore, classification outputs can be constrained, such that the order of changes in behaviors are logical. The classification output for each fix of the trajectory is first checked with the labels of surrounding fixes, to ensure a certain logical flow in the extracted classes.

This has been studied well in other research fields, including image classification (Kohli et al. 2009), remote sensing (Schindler 2012; Benedek et al. 2015) and body-pose recognition from depth images (Shotton et al. 2013). The idea is to enforce the smoothness of classification outputs by estimating *a posteriori* knowledge on the results. Similarly in movement studies, this knowledge should be integrated into the methods developed, a principle that has however been mostly disregarded in the existing methods reported in the literature. Therefore, as part of future work, the potential of dependency-aware methods for movement analysis such as belief propagation may be exploited, where the trajectory is considered as a Markov chain and an estimation of maximum *a posteriori* probability will be given concurrently with the initial classification results. Belief propagation methods represent a class of techniques to consider pairwise cliques between neighboring fixes to enforce the dependency in the changes of movement characteristics, by maximizing the posterior knowledge over the entire trajectory.

6.4.3 Outlook

Movement trajectories are a novel source of geographic data, having practical applications in a variety of academic and business fields these days. Unprecedented volumes of such data has given rise to emerging fields of research (i.e. computational movement analysis and urban computing), where analytical methods meet conventional geographical disciplines, aiming to tackle issues in those area. It is expected that real-time analysis of such data will become more common in the future. Therefore, development of sophisticated analytical tools capable of applying on large volumes of trajectory data is necessary.

Apart from technical issues, what remains as the main challenge is finding behavioral insights in order to get value from this new source of data. The data will stay untapped unless behavioral insights are extracted. The obtained results in this thesis bring new perspectives for the analysis of movement data. Shifting from scale-specific methods to cross-scale analysis approaches are highly important to reveal such behavioral insights. Considering the fact that technology has had a huge impact on development of cross-scale analysis in other geographic applications, it is expected to witness more research on cross-scale analysis of movement data in the future. However, it has to be noted that employing cross-scale analysis is labor-intensive and if researchers are already aware of the behavioral insights, they may not bother themselves to get further insights by conducting such analysis.

Despite the fact that cross-scale analysis was only performed in two movement analyses (i.e. movement classification and trajectory segmentation), it is highly decisive to consider cross-scale analysis in other problem settings. Therefore, for future movement analysis studies, it is important to think of integrating cross-scale analysis in the proper stage of the analysis depending on the problem being addressed. As was demonstrated in this thesis by employing different real-world and simulated datasets, scaling issues manifest themselves in different ways in movement analysis and therefore appropriate methods need to be used to provide relevant results in response to scaling effects.

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(***Note:*** This bibliography is related to Introduction and Synthesis chapters. For the bibliography of individual papers, reader is referred to the corresponding chapters)

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- **Soleymani, A.**, Pennekamp, F., Dodge, S. and Weibel, R. (2016). Characterizing change points and continuous transitions in movement behaviors using wavelet decomposition. *Methods in Ecology and Evolution* (under review).
- **Soleymani, A.**, Pennekamp, F., Petchey O.L. and Weibel, R. (2015). Developing and integrating advanced movement features improves automated classification of ciliate species. *PLoS ONE*, 10(12): e0145345.
- **Soleymani, A.**, Cachat, J., Robinson, K., Dodge, S., Kalueff, A. V. and Weibel, R. (2014). Integrating cross-scale analysis in the spatial and temporal domains for classification of behavioral movement. *Journal of Spatial Information Science (JOSIS)*, 8(8), 1-25.

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- **Soleymani, A**. and Weibel, R. (2014): Extraction of movement features for cross-scale behavioral classification. Workshop on Analysis of Movement data, GIScience 2014 Conference, Vienna, Austria.
- **Soleymani, A.**, van Loon E. E. and Weibel, R. (2014). Capability of movement features extracted from GPS trajectories for the classification of fine-grained behaviors. AGILE'2014 International Conference on Geographic Information Science, Castellon, Spain
- Samadzadegan, F., **Soleymani, A**. and Abbaspour, R.A. (2010). Evaluation of Genetic Algorithms for Tuning SVM Parameters in Multi-Class Problems, 11th IEEE International Symposium on Computational Intelligence and Informatics (CINTI2010), Budapest, Hungary
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